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Design and Investigation of a Multi Agent Based XCS Learning Classifier System with Distributed Rules

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Contents

Introduction

The concept of Learning Classifier Systems (LCS) has been introduced in 1976 by John H. Holland. LCS are adaptable machine-learning algorithms that are applied in fields such as data-mining, robot control and modeling and optimization. Since its emergence the concept of LCS underwent multiple changes and enhancements and a wide range of different systems has been developed. One remarkable system that constitutes the basis of this thesis is the eXtended Classifier System (XCS), introduced by Stewart W. Wilson in 1995.

It is the goal of a LCS to reach a certain environmental state by executing certain actions. To determine the action to execute, a LCS contains a collection of rules that represents the knowledge the system has acquired. A single rule is also called a classifier. When being confronted with a problem, the LCS makes decisions based on its population of classifiers. It perpetually updates and improves that population to make better decisions in the future. Such a classifier population usually contains thousands of classifiers in a single set. The problem to be dealt with in this thesis is the development of a LCS that can potentially be applied in distributed memory-constrained environments such as Wireless Sensor Networks (WSN). A single node in a WSN or any other distributed architecture might not have enough memory to keep track of thousands of classifiers. This thesis introduces a LCS that is able to handle such constraints imposed by certain distributed architectures.

With technology moving more and more towards parallelism and distribution, observable in the emergence of multi-core processors, cluster computing, network applications and more, a reliable LCS resembling and adapting to distributed architectures could provide a huge benefit. The work presented here constitutes an attempt of developing a coherent, powerful Learning Classifier System, applicable to real world problems, that handles its knowledge in a distributed way.

The introduced LCS has been realized by adapting an implementation of Wilson's eXtended Classifier System (XCS). The introduced architecture splits the population of classifiers into subsets, so called agents. To make sure such a system works appropriately, minor and major changes have necessarily been applied to almost every part of the original XCS. The biggest challenge was not to adapt XCS basic architecture but to ensure the proper interaction of all adapted components.

The basic unit of every LCS is the single classifier. A classifier consists of a condition and action part. For any given problem instance that is posed to the system, a classifier proposes its action if the input matches the condition. Usually, there are several classifiers with matching conditions that are proposing different actions. The classifiers compete against each other for activation and the system executes the action that is expected to reap the highest reward. The received reward is distributed between all classifiers that have contributed to the outcome. The population of classifiers is constantly updated and improved towards more accurate solutions. This is achieved by a credit assignment mechanism and a Genetic Algorithm (GA). The GA selects classifiers from the population, replicates them and performs genetic operators such as crossover and mutation to create new classifiers. Such newly created classifiers are inserted into the population and older, badly performing classifiers are deleted. Hence, a LCS evolves a more and more accurate solution as it classifies more problem instances.

The main problem to be solved by this work is to alter the architecture of XCS in a way that its knowledge is distributed among several agents. These agents have to be interacting efficiently to classify a given problem instance. An agent is supposed to be able to decide whether to classify that problem instance himself or to delegate it to another agent that seems better suited to that specific problem instance. It is desired that a problem instance passes as few agents as possible and is still being classified correctly. Further more, such an altered structure of the population has to be incorporated into the credit assignment mechanism, the GA and all other components. This is necessary for the system to be able to evolve accurate solutions and communication structures between the agents. The resulting system is supposed to preserve most of XCS simplicity while reaching similar classification performance.

As mentioned earlier, such a system could potentially be implemented in

distributed environments. Consider a Wireless Sensor Network (WSN) where the architecture of several memory-constrained nodes resembles the architecture of the classifier system that will be introduced in this thesis. In a WSN that applies such an adapted XCS, classifiers would be distributed among all nodes and only a few relevant nodes would have to contribute to the classification of a given problem instance. Such a solution does not only extend the concept of Learning Classifier Systems, making it better suited to distributed environments, it also shows the general capability of LCS to evolve complex structures that go beyond the straight problem solution.

To facilitate such interacting agents, the concept of the single classifier had to be enhanced. The action part of the single classifier has been extended, enabling delegations to other agents. Hence, classifiers are no longer only proposing actions on the environment, but also delegations to other agents. A problem instance is posed to one agent at a time. Within such an agent, the expected reward is determining whether to classify the problem instance or to delegate it to another agent that seems more suitable. Hence, a problem instance is being passed from agent to agent until a classification that expects high reward can be executed. All original components had to be adapted to facilitate this kind of behavior. Classifiers that are delegating problem instances to well suiting agents are rewarded by the system. The GA replicates and evolves delegating classifiers similarly to traditional classifiers and performs the same genetic operators on them. Also, the system takes care that no agent contains too many classifiers as space is limited. The introduction of all these changes led to the adapted XCS that is established and analyzed in this thesis, eXtended Classifier System - Distributed Rules (XCS-DR).

Chapter 1 provides all the necessary background information to understand the concept of Learning Classifier Systems. It introduces the common components, gives a short overview of the historic development of the field and discusses work that is related to that thesis. Chapter 2 explains Wilson's XCS in greater detail. It provides an extensive descriptions of XCS' components and how these are interacting to solve a given problem. A thorough understanding of XCS and its vital mechanisms is necessary to grasp the changes introduced in the subsequent chapter. Chapter 3 introduces XCS-DR, the agent-based extension of XCS. It provides insights about how exactly the distributed architecture has been realized and what problems had to be dealt with. The subsequent chapter

discusses and explains the Java implementation of XCS-DR. The overall structure of the program is provided as well as explanations about how to modify the source code and run the program. The last chapter, chapter 5, evaluates XCS-DR's performance. It illustrates how accurately XCS-DR performs compared to the original and how different configurations and problems posed to the system affect performance.

Chapter 1

Prerequisites and Background

This chapter provides the necessary background information to grasp the concept of Learning Classifier Systems. First, it is the general framework introduced that includes the definition of a single classifier, the basic workflow of a LCS and the interacting components. Next, some historic background of the field of LCS is provided and at last it is discussed related work.

1.1 General Framework

There is not a totally clear-cut definition of what a Learning Classifier System (LCS) is since manifold different kinds of LCS exist, with different underlying models, suited to various problem types. Learning classifiers are machine learning algorithms able to solve complex and perpetually changing problems. They are rule-based systems interacting with an environment and adapting to it in order to maximize a certain kind of reward. The basic LCS framework combines ideas from different fields of research such as artificial intelligence, evolutionary theory and machine learning [44].

In general, all Learning Classifier Systems apply two learning and optimization techniques, gradient-based approximation and evolutionary optimization. Both interact to locally approximate a function and improve that approximation over time [4]. Gradient-based approximation addresses the local approximation of a target function. It is optimizing the prediction value of a single classifier and therefore providing a local fitness quality estimate for it. However, evolutionary optimization is aimed towards improving the structure and accuracy of the overall classifier population using the fitness estimate provided by the gradient-

based approximation. Through the evolutionary optimization all classifiers in a population compete against each other for survival and replication. The new classifiers generated by the evolutionary optimization technique are also to be evaluated by the gradient-based approach.

Learning Classifier Systems are applicable to a wide range of problems such as robot control, function approximation, data mining and more [4].

1.2 The Classifier

The basic building block that every LCS applies in one way or another is the concept of a classifier. This is also referred to as a rule. A single classifier represents a piece of knowledge about the problem to be solved by the system. A classifier typically consists of a condition C, action A, prediction p and might have additional parameters such as fitness, prediction error, etc. associated with it. The environmental input state, that all classifiers are being compared to, is typically represented as a bit vector. The general interpretation of these structures is that if condition C is satisfied by a certain input and its proposed action A is executed, a reward of the prediction value p can be expected. Usually $C \in \{0, 1, \#\}^L$ where $\#$ is defined as the "don't care" symbol and L is the length of environmental input. If there is a $\#$ symbol at a certain position in the condition, it matches with both 0 and 1. Therefore, it does not matter whether the input vector is 0 or 1 at that particular position. The action part $A \in \{a_1, a_2, \ldots, a_n\}$ defines the action that a classifier proposes if matched.

Example:

- Input: 0110
- Classifier: $01\#0 : a_1 \quad p = 100$

The classifier's condition matches the input and proposes action a_1. A reward of 100 is expected if action a_1 is executed

1.3 Basic Workflow

In a standard LCS detectors translate the environmental state into input messages. Any classifier of the population that matches the input message proposes

its action. The LCS puts all matching classifiers into a match set and further creates a situation where all classifiers in that set bid to be activated. Generally, the more credit a rule has accumulated the more likely it is for it to be activated. The term strength is used to refer to the amount of payoff a classifier has accumulated. For any given input message the system selects the action that is expected to reap the highest reward. After selecting an action the LCS creates an action set from the match set that contains all classifiers proposing the selected action. The chosen ation is then translated into actions on the environment by effectors. In certain situations the environment provides a reward for good decisions. The reward is being distributed between all classifiers in the action set. Every certain steps a Genetic Algorithm becomes active, searching for new, more effective rules and deleting ineffective rules.

Example:

- A resource collecting robot is in front of some kind of resource. The sensors of the robot translate that environmental state into an input message. The input message is compared to all classifiers. Some matching classifiers propose turning around. Some classifiers propose collecting the resource and others propose other actions. The combined payoff prediction for the classifiers that propose collecting the resource is the highest. Therefore the system selects that action. The reward is received immediately in the form of resources and distributed among all classifiers in the action set.

1.4 Components

There are four basic components that are common for almost all LCS [44]:

Performance Component The performance component is responsible for interacting with the environment. It receives environmental input, sends back the chosen action and receives reward for good choices.

Knowledge Representation Every LCS manages one or more sets of rules that are making up the entire classifier population of the system. This is the core of every LCS since the classifier population represents a model of the environment and thus embodies the current knowledge of the system. There are

two different types of LCS regarding the classifier population. A Michigan LCS is characterized by a single population of rules whereas the Pittsburgh approach evolves multiple competing rule sets. The LCS that are subject of this thesis are of Michigan type. A single classifier in the population is simple, containing only a very limited amount of knowledge. It is their combined activation that makes it possible for them to handle complex and novel environmental states. As Holland stated *"there wont be a enough single monolithic rules to handle situations like 'a red Saab by the side of the road with a flat tire' but it is handled by simultaneously activating rules for the building blocks of the situation: 'car', 'roadside', and the like."* [29, p. 4]. Knowledge representation is often considered to be part of the performance component.

Credit Assignment The environment provides reward in certain situations if competent decisions have been made by the LCS. For instance if after multiple steps a robot is able to collect resources from a source, it is rewarded for the success. It is the credit assignment component's task to determine the payoff amount and distribute it between classifiers. For this purpose the LCS keeps track of the performance of every single classifier and is able to assess its future success through a prediction parameter. The goal is to reward classifiers that have contributed to the current reward. However, many classifiers might be active at the same time. A major problem is to distinguish between classifiers that actually contributed to the positive outcome and others that have been ineffective or even obstructive. Another challenge for the credit assignment mechanism is to provide a fair payoff also for classifiers that did not seem like good decisions at the time they were being active but set the stage for later success. A rewarded classifier shares its payoff with preceding classifiers that made its activation possible. However, different LCS apply various different variants of distributing credit between the classifiers. Possible approaches are the traditional bucket brigade algorithm, supervised learning, Q-Learning and more. The credit assignment unit is also referred to as reinforcement component.

Discovery Component A LCS needs a mechanism of evolving its classifiers towards better solutions for the environmental input. Classifiers that are working incorrectly should be replaced and valuable classifiers should be replicated. Also new classifiers should be created to explore the problem space. Generating

classifiers randomly is not effective for problems of a certain size. Therefore a more sophisticated approach is necessary to address this issue. The goal of effective rule discovery in LCS is usually addressed through a Genetic Algorithm (GA). GAs [16, 19] apply concepts from biological fields such as evolutionary theory and are based on ideas such as natural selection. The GA uses the fitness parameter of each classifier to determine its replication value. Classifiers with a higher fitness are less likely to be replaced and more likely to be reproduced. For the generation of classifiers, the GA makes use of genetic operators such as Cross-Over, Mutation and Selection. A particular GA is described in further detail in the next chapter. There have been introduced manifold different kinds of GAs. Today, the concept of niche-based GAs in contrast to panmictically acting GAs is widely adopted, making the search for new classifiers more precise. A niche GA is not active on the whole population of classifiers but only on a subset of it (e.g. match set, action set). It avoids creating competition between otherwise unrelated classifiers [44]. While it is common for most LCS to rely on a GA, there have been proposed alternative, "non-evolutionary" implementations of a discovery component based on different search heuristics (i.e. [38, 43]).

1.5 Problem Types

Butz stated that "*despite their somewhat misleading name, LCSs are not only systems suitable for classification problems, but may be rather viewed as a very general, distributed optimization technique*" [4, p. 961]. LCS in general are able to solve classification problems, problems originating the field of reinforcement learning (RL), function approximation and general prediction problems.

Every specific problem can be characterized as either a single-step problem or a multi-step problem. In a single-step problem reward is received immediately after an action was executed (i.e. Boolean Multiplexer Problem). In those kinds of problems successive situations are not related to each other and therefore the environment is providing reward independently for every situation. In a multi-step problem several successive situations are related to each other and feedback is provided delayed only after a certain satisfactory environmental state has been reached (i.e. Maze Problems).

Classification Problems In a classification problem there is a set of problem instances with each instance belonging to a certain class. It is the LCS' task to classify all instances of a given problem type with maximum accuracy. The solution found by the LCS is supposed to be a general problem solution, meaning that other unseen instances are classified correctly also. Classification problems are single-step problems. Typical classification problems are boolean functions (e.g. Boolean Multiplexer), image classification or medical diagnosis.

Reinforcement Learning Problems originating RL are usually multi-step problems. LCS have been applied to two types of Sequential Decision Problems called Markov decision problems (MDP) and partially observable Markov decision problems (POMDP) [3]. The POMDP are not discussed further in this thesis. For a detailed introduction regarding POMDP and LCS see [3]. A MDP is *"the problem of calculating an optimal policy in an accessible, stochastic environment with a known transition model"* [39, p. 518]. An accessible, stochastic environment is an environment where the transition between states is dependent only on the choice of a certain action and a certain state-dependent transition probability and not on previous actions. The environment is accessible if at each step the agent is able to perceive the current state it is in (e.g. robot receiving sensory input). The term policy defines a complete mapping from any state to a certain action. The LCS' ability to find the optimal action (the action that is expected to reap the maximum reward) in any given state is equal to calculating an optimal policy and therefore solving the MDP.

There is also a class of problems called non-Markov decision problems (non-MDP) that are harder to solve than MDPs. The difference is that for an agent in a non-MDP the transition between states is not only dependent on the chosen action and the state-dependent transition probability but also on past states the agent was in. Non-MDPs are not solvable by traditional LCS since they do not have the ability to store information about past states. But there have also been LCSs investigated dealing with non-MDPs such as ZCSM and XCSM [6, 34]. Their ability to handle non-MDPs stems from the addition of memory that stores limited information regarding previous states. Typical RL problems are maze problems or block world problems. A maze task is characterized by some agent that has to find resources in a maze. In block world problems, moving blocks to a certain constellation in a block world leads to success.

Function Approximation Problems Approximate the value of a function by a set of partially overlapping approximation rules. E.g. Arctangent, polynomials, etc.

General Prediction Problems Any problem where a certain reward value has to be predicted.

Generally, there are two ways a LCS can be applied to a problem. It can be used either in online or offline mode. Online mode presents the training instances to the system one at a time. The system's classifier population is subject to constant evolution, changing continuously at all times. Michigan LCSs typically apply this approach. In contrast to that, offline learning systems have a distinguished training phase where all the training instances are presented to the system and the classifier population evolves. After training the rule set is fixed and applied to the problem. Offline learning is often used for data mining problems. Pittsburgh LCSs evolve multiple rule sets during training phase which enables them to find a better solution with less training instances in some cases compared to a Michigan LCS. But the fact that they are evolving multiple competing rule sets with only one being applied to the problem after training restricts them to offline learning only. Therefore the Michigan approach can be applied to a broader range of problem domains being able to solve problems online and offline. Also due to the smaller population of rules at all times in a Michigan LCS (only one rule set exists) it can be applied to bigger, more complex tasks.

1.6 Historic Remarks

The original Learning Classifier System concept was introduced in 1976 by John H. Holland in [20]. In the beginning it was simply called classifier system. Holland's more well-known invention, the Genetic Algorithm [19], was developed one year earlier. In the 80s the now common name Learning Classifier System prevailed [37]. Holland's first implementation of a classifier system, Cognitive System One (CS-1) [30], was the first one to merge a Genetic Algorithm with a credit assignment scheme to evolve a set of rules as a problem solution. It was developed at the University of Michigan and would establish the founda-

tion for a whole branch of LCS called "Michigan-style" LCS. In comparison the dissertation of Smith in 1980 at the University of Pittsburgh [41], introducing LS-1, inspired what would be called "Pittsburgh-style" LCS. The basic distinction between both systems can be found in their population of rules. Where the "Pitt-approach" is characterized by multiple variable length rule-sets, each representing a solution to the problem, the "Michigan-style" LCS is characterized by a single rule-set. In the 1980s Holland further investigated and improved the concept of learning classifiers [21, 22, 23, 24, 25, 26, 27, 28]. He was first to apply the later widely adopted bucket brigade algorithm (BBA) [26] for credit assignment. Meanwhile specific GAs were scrutinized in detail as well. Booker proposed the use of a niche-based GA on a system based on CS-1 [1]. In a niche GA the GA only acts on small sets of rules, e.g. the match set, instead of the whole rule population. In 1986 Holland introduced his hallmark LCS, Standard CS [22], that would become the benchmark to compare against for many future LCS. Between the late 80s and the mid 90s research activity slowed down on the field of classifier systems. This was mainly due to the systems inherent complexity that made them hard to understand and their still narrow range of applications [44].

The introduction of Q-Learning in 1989 [45] and the publication of ZCS by Wilson in 1994 [47] constituted a revolution for the field of leaning classifiers that brought it back to life. Q-learning, perhaps the most widely used reinforcement learning algorithm to day, could be applied as a much better way of payoff distribution between classifiers. Wilson's ZCS, Zeroth Level Classifier System, was a system with a much simpler architecture than its predecessors and the first one to apply a credit assignment scheme resembling Q-learning. It dismissed the more complicated but also more common Bucket Brigade algorithm. One year later, with the introduction of an eXtended Classifier System (XCS) [48], Wilson introduced what would become the most thoroughly studied and best understood LCS to date. XCS was the first LCS to apply accuracy based fitness combined with a niche GA compared to the more commonly used strength-based fitness at that time. It was a simple LCS with superior performance to earlier more complex implementations. The XCS evolves maximally general and accurate rules.

In the following years new kinds of LCS have emerged. In 1998 Stolzman laid the foundation for a new family of LCS called Anticipatory Classifiers by

introducing ACS [42]. ACS extended the classic framework by also anticipating changes to the environment after a certain action has been undertaken. It is able to predict the consequences to the environment of a certain action in a certain situation. Therefore rules are represented in the form of condition-action-effect. The ACS architecture proved useful for speeding up learning, planning and more. Further research of Wilson led to the introduction of XCSF [50], a classifier system for function approximation.

More recently, distributed LCS and LCS dealing with non-Markov problems have been investigated in more detail. DXCS developed by Dam et al [7, 8, 9] for example deals with multiple XCS instances to solve data mining problems.

Since this thesis point of emphasis is mainly built on Wilson's original XCS, further, recent accomplishments in other areas of the field of LCS are not introduced here.

1.7 Related Work

There has been put a lot of work in exploring Classifier Systems working with multiple instances or agents. Three distinct areas of research have become apparent. There has been put effort into developing Multi-Classifier Systems (MCS) that are characterized by the combination of multiple distinct LCSs to yield better classification results [36]. Ranawana and Palade found out that for large datasets with a certain level of noise involved, researchers have been unsatisfied with the classification accuracy by a single LCS. This circumstance led to the idea of combining several distinct LCS. Due to noise being involved it is hardly possible to engineer one perfect LCS suitable for all problem instances of a given domain. But combining different machine learning paradigms to solve the same problem can lead to better results due to the different processing of the data. For that approach to be successful it is important that the classifiers are sufficiently diverse, not always providing similar results. This is rather intuitive since, with all classifiers being equal, no improvements can be made by combining them. Another need for a MCS to work is that each classifier has to have an accuracy of at least 50%. Important for the success of a MCS is the selection criterion. There are various possible combiner functions to determine the output such as SUM, majority voting or Bayesian combination. To organize the classifiers, different topologies have been applied, such as parallel or cascad-

ing topology. The combinations of different LCS have been scrutinized, among others, by [11, 12, 15, 32].

An area that among other approaches deals with multiple LCS instances is ensemble learning. Dam et. al have developed a system called DXCS [7] which consists of multiple instances of XCS to solve distributed data mining problems (DDM). They are addressing the problem of classifying big aggregates of data located in different places. To avoid heavy network traffic and security issues involved in sending big amounts of data over a network DXCS uses several client XCS instances that are interacting with a central server XCS. The clients classify their raw data and send their derived model to the server XCS. The server applies an approach called knowledge probing [18] to assemble a consistent model of the clients classifications. This concept has also been extended for other LCSs, called DLCS [10]. In the field of ensemble learning and DDM there have been investigated various other approaches as well [13, 17, 31, 33].

Gershoff and Schulenburg examined the performance of multiple hierarchically interacting XCS agents (CB-HXCS) [14]. CB-HXCS makes use of a hierarchy of XCS instances so that every instance only acts on a subdomain of the given problem. For CB-HXCS to work it is necessary for the environment to be partitioned into subspaces. At the bottom of the hierarchy are multiple base level agents that consist of several XCS instances, so called micro-agents. To each base level agent is assigned an environmental partition. For a given problem instance the base level agent decides the output signal by collecting votes from its micro-agents. A simple majority vote is taking place. The base level agents also emit information on the confidence of their decisions based on the voting. After voting the majority signal is exposed to one or more appropriate meta agents. This process repeats until the top of the hierarchy is reached. The top level meta agent emits the final classification. Experiments have shown that in some situations CB-HXCS solved classification problems more efficiently than a standard XCS.

The work that constitutes the original inspiration for the topic of this thesis, although not closely related to XCS, is [40] by Scheidler and Middendorf. In their paper, a multi agent Pittsburgh LCS is introduced and examined. The main characteristic of this system is that it extends the action part of the single classifier. In contrast to conventional classifiers, the possible action values do not only include all possible actions on the environment but also delegation actions

that forward the input to other agents. Also every agent has restricted classifier storage capacity and therefore can only keep a certain maximum number of classifiers. Both these changes to the classic LCS framework are adopted in this thesis and applied to XCS. In training phase every agent keeps multiple rule-sets choosing the best one for deployment after training phase finished. The system had to solve several problems, such as the Incremental Multiplexer Problem and the Incremental Parity Problem. Scheidler and Middendorf not only examined its accuracy, but also the evolving delegation patterns in a ring topology, grid topology and fully connected agents with different communication penalties. It was observed that with communication costs being zero, a clear distinction between delegating and classifying agents could be made. In contrast to high communication costs, where much less delegation took place and classification was distributed evenly between agents.

Chapter 2

XCS

This chapter provides a brief description of XCS, the specific classifier system to build on in this thesis. Since its publication, XCS has been subject to manifold investigations, advancements and refinements due to its simple architecture and superior performance compared to previous LCS. This chapter provides an overview of XCS' components and core concepts as well as of its inner workings. Also, the Java implementation XCSJava 1.0 developed by Martin V. Butz is introduced in short, since this code constitutes the foundation for the extension introduced in the following chapter.

2.1 Which XCS to Build On

There have been various kinds of XCS developed since its first publication. The main work of this thesis builds on and extends the XCSJava 1.0 source code and therefore the specific XCS implemented by XCSJava 1.0 is explained here. XCSJava 1.0 is close to the original system explained in [48] with a couple of modifications. The modifications implemented by XCSJava 1.0 are mainly the ones introduced in [5]. According to the documentation of XCSJava 1.0 [2] it is implemented as close to [5] as possible. This chapter not only describes the XCS outlined in [5] but also points out the few differences between this system and XCSJava 1.0. At the beginning of the work, the original source code of XCSJava 1.0 could be downloaded from ftp://ftp-illigal.ge.uiuc.edu/pub/src/XCSJava/XCSJava1.0.tar.Z. Unfortunately, at the time of writing the server is not online anymore and there is no other place to download XCSJava 1.0 from.

2.2 Strength vs. Accuracy

In most LCS developed prior to XCS, the strength of each classifier was the central parameter to maintain. Strength constitutes a payoff prediction of the classifier, if its condition is matched and its proposed action executed. It is often referred to as prediction. Strength is an important quantity for a LCS to find the most profitable action since it provides a prediction of the payoff that a classifier is receiving. Moreover, in previous systems strength has been the basis to determine a classifier's fitness in the GA. Classifiers with higher strength had a higher probability to replicate and a lower probability to be deleted. However, Wilson identified several problems associated with using the strength value as a fitness estimate. First, there might be different payoff levels in different niches of the problem space which can lead to the takeover of classifiers in high-profit niches. Second, the GA is unable to make a difference between highly accurate classifiers in low-payoff niches and overgeneral classifier generating the same average payoff. Further more in strength-based GAs there has no tendency been observed towards accurate generalizations. For a more detailed discussion of the problems associated with strength as a fitness quality estimate see [48]. The observed problems lead Wilson to redefine a classifier's fitness in XCS by taking accuracy into account. He replaced the strength parameter with three new ones: a *prediction* parameter p to measure the average payoff received, *prediction error* ϵ that measures the error of the prediction parameter and *fitness* F, an inverse function of the prediction error. The *fitness* parameter is the one used by the GA to determine a classifier's replication and survival value for the system. This approach avoids encouraging overgeneral classifiers with low accuracy. Further more it tends to form a complete mapping $X \times A \Rightarrow P$ from the product set of the problem space and possible actions to payoff. Therefore, the system does not only converge on what seems to be the best solution but explores the consequences of every action. This is due to the property that highly accurate classifiers survive and replicate even if their expected payoff is very low.

2.3 Components of XCS

Figure 2.1 shows an overview of XCS' parts and components and how they are interacting to form the working system. Central aspects are the additional

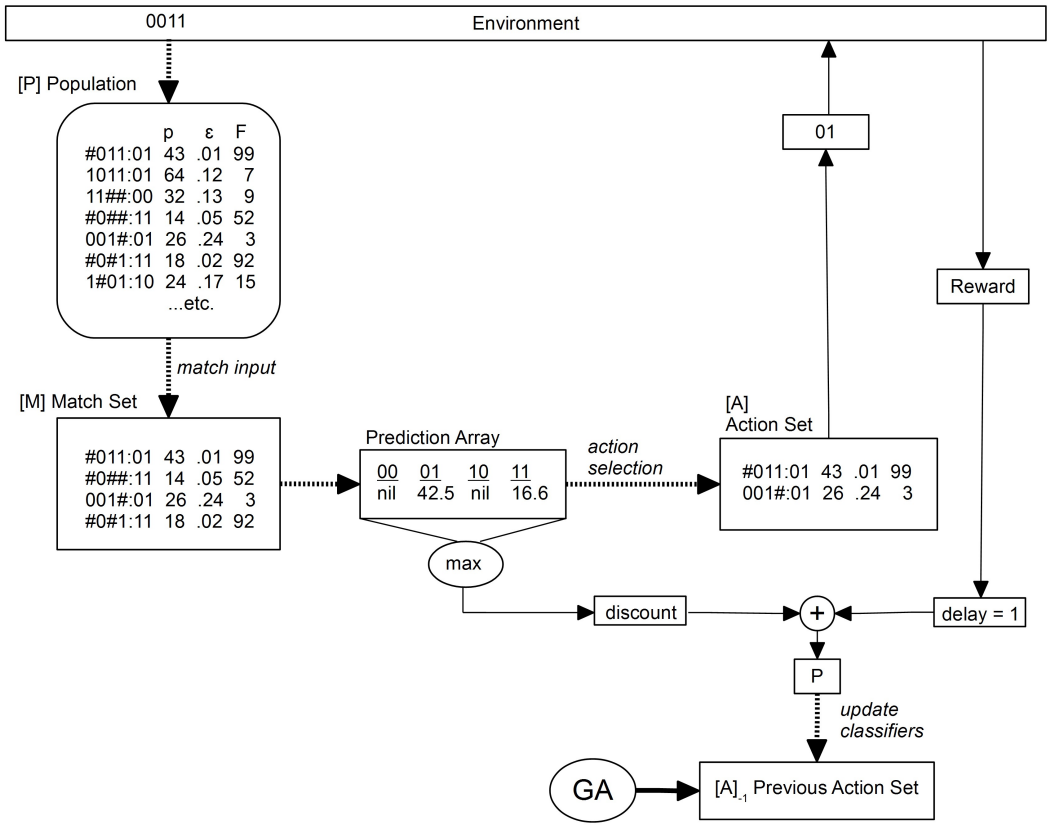


Figure 2.1: XCS system overview. For a given input, the match set and prediction array are formed, which are used to determine the action to execute and form the action set. The received payoff is used to update the previous action set via Q-learning. (This figure has been created after figure 1 in [48])

fitness parameter and prediction error parameter associated with each classifier in the population and the way the prediction parameter is updated by the credit assignment unit. The single components and their interactions are pointed out in more detail in the following sections.

2.3.1 The Classifier

As noted earlier, each classifier in XCS has a *prediction* p, *prediction error* ε and a *fitness* F associated with it. In addition to these, each classifier keeps track of an *experience, action set size* and *time stamp* parameter. The *experience* parameter is used to keep track of how often a classifier was part of an action set. Its value determines the way certain parameters are updated. The *time stamp* dictates the invocation of the GA. The *action set size* affects the probability by

which a classifier is deleted from the population.

Other than that is every classifier implemented in XCS as what is termed a macro-classifier. This means that even if a classifier occurs twice or more in the population there is only one macro-classifier that keeps track of its quantity by a *numerosity* parameter. Whenever an already existing classifier is generated and inserted in the population only the existent classifier's numerosity is incremented. So instead of N identical classifiers, there is one classifier with numerosity N kept in the population. The concept of macro-classifiers is just a programming technique used to speed up matching. All procedures treat macro-classifiers as if they were multiple traditional classifiers.

2.3.2 Performance Component

The Different Sets

- The population $[P]$ represents the actual knowledge of the system. It contains all existing classifiers. Its size is fixed.
- The match set $[M]$ is formed each cycle by comparing the input state with every classifier in $[P]$ and adding all matching classifiers to $[M]$.
- The action set $[A]$ is formed by adding to it all classifiers from $[M]$ that propose the action selected for execution.
- The previous action set $[A]_{-1}$ is maintained in the system every cycle to update its classifier's parameters.

The Prediction Array As noted above, $[M]$ is formed by matching the input with the population. To find the best action to execute, XCS generates a prediction array that has an entry for every possible action. The prediction array associates an expected payoff with every possible action. Therefor it calculates the fitness-weighted average of the predictions of classifiers in $[M]$ proposing the same action. Actions that are not present in $[M]$ get the value *nil* associated with them in the prediction array.

Assume there are n classifiers proposing action a_k in $[M]$. The associated predictions and fitnesses are p_1, p_2, ..., p_n and f_1, f_2, ..., f_n. In that case the

entry $P(a_k)$ for action a_k in the prediction array is calculated as follows:

$$P(a_k) = \frac{\sum_{i=1}^{n} p_i * f_i}{\sum_{i=1}^{n} f_i} \tag{3.1}$$

This value is computed for every action that occurs in a classifier of the match set.

Action Selection After forming the prediction Array XCS decides which action to execute. There are different possible ways to determine such an action. In this system two approaches are applied. One is choosing the action with the highest prediction in the prediction array and the other one is choosing an action randomly. There are two different modes of execution, explore and exploit, and each of them is associated with one of the action selection schemes. See section 2.6 for further explanation.

2.3.3 Reinforcement Component

The reinforcement component is assigned with distributing payoff and updating all classifiers of the previous action set $[A]_{-1}$. Every time a classifier belongs to $[A]_{-1}$ its parameters are updated. The update mechanism is activated right after an action has been executed and payoff received. The order in which the updates occur is *experience*, *prediction error, prediction, action set size,* and *fitness* which differs from the original system. Note that in single-step problems, such as the multiplexer problem, the update procedure is executed on the current action set $[A]$ since consecutive steps are not related.

Updating Prediction To update a classifier's prediction, the Reinforcement Learning technique Q-learning is applied. Wilson first implemented Q-learning in a LCS in ZCS [47]. After the execution of a selected action, payoff is received. The current payoff and the maximum prediction value of the prediction array $P_{\max}$ are used to calculate the quantity P: $P = reward + \gamma P_{\max}$. The discount factor γ is set to 0.95 in XCSJava 1.0 which is different from the 0.71 suggested in [5]. For single-step problems it is $P = reward$.

After calculating P, that value is used in combination with the Widrow-Hoff delta rule [47] to update the prediction p_j of each classifier in $[A_{-1}]$ ($[A]$ in

single-step problems):

$$p_j \leftarrow p_j + \beta\,(P - p_j)$$

. The learning rate parameter β is set to 0.2 in XCSJava 1.0. It establishes the impact a single update has on the classifier's prediction. Note that the Widrow-Hoff rule is used only when a classifier has an experience of at least $1/\beta$. Otherwise *"the new values in each case are simple averages of the previous values and the current one"* [48, p. 153]. The applied formula, with experience exp_j of cl_j is:

$$p_j \leftarrow \frac{p_j\,(exp_j - 1) + P}{exp_j} \tag{3.2}$$

This two-phase technique is called moyenne adaptive modifée (MAM). According to [48, p. 153] this *"makes the system less sensitive to initial, possibly arbitrary, settings of the parameters"*. MAM is applied to the update of the prediction, prediction error and action set size parameters. When XCS was first introduced in [48], MAM has also been applied to the fitness update.

Fitness Calculation A classifier's fitness is updated on the basis of its relative accuracy. First, for a classifier c_j in $[A]_{-1}$ ($[A]$ for single-step problems) its accuracy k_j is computed. XCSJava 1.0 applies Wilson's power function published in [49]:

$$k_j = \alpha \left(\frac{\varepsilon_j}{\varepsilon_0}\right)^{-\nu}$$

for $\varepsilon_j > \varepsilon_0$ and $k_j = 1$ otherwise. Thus, if a classifier's prediction error is smaller or equal to ε_0, its accuracy is set to 1. ν is set to 5 in XCSJava 1.0. In the ensuing step, the relative accuracy $k_j^{'}$ is computed by dividing k_j by the total of the accuracies of the classifiers in $[A]_{-1}$ ($[A]$ for single-step problems). For s macro-classifiers in $[A]_{-1}$ (resp. $[A]$) and n being the *numerosity* of a macro-classifier:

$$k_j^{'} = \frac{n_j * k_j}{\sum_{i=1}^{s} n_i * k_i}$$

. At last, the Widrow-Hoff formula is applied to update the fitness F_j of cl_j with its relative accuracy:

$$F_j \leftarrow F_j + \beta\left(k_j^{'} - F_j\right) \tag{3.3}$$

In contrast to [48] is the MAM technique not used for the fitness update in XCSJava 1.0.

Remaining Parameters The prediction error of a classifier c_j, ε_j is adjusted using the MAM technique with the according Widrow-Hoff rule: $\varepsilon_j \leftarrow \varepsilon_j + \beta\,(|P - p_j| - \varepsilon_j)$. Section 2.3.3 clarified how P is computed. The same procedure is applied to the update of the action set size as_j of classifier c_j, with the according Widrow-Hoff formula: $as_j \leftarrow as_j + \beta\,(cs - as_j)$. The quantity cs marks the current action set size. All these parameter updates apply the MAM technique. Consequently, in case of $exp_j < \frac{1}{\beta}$, formula 3.2 is applied, with the according parameter to be averaged.

The experience of each classifier is incremented as soon as the update procedure begins.

2.3.4 Discovery Component

Genetic Algorithm The Genetic Algorithm occurs after the reinforcement component finished updating parameters. It is a niche GA acting only on the action set. The time stamp parameter of each classifier marks the last time it was part of an action set where the GA was active on. The GA acts only occasionally on the action set, when the difference between the average of all classifier's time stamps in the action set and the current counter exceeds a threshold θ: $actual\ time - time\ stamp\ avg > \theta$. θ is set to 25 in XCSJava 1.0. When the GA becomes active it selects two classifiers from the action set via roulette wheel selection. The relation of a classifier's fitness to the total of the fitnesses of all classifiers of the action set constitutes its selection probability. Thus, in this selection method is the probability for a classifier to be selected proportionate to its fitness value. See [5] for a detailed description in pseudo-code. Both selected classifiers are copied and with a certain probability there is a two-point crossover performed on them. The two-point crossover procedure randomly chooses a number between 0 and the length of the classifier's condition for each classifier. The parts of each classifier's condition that are located between these two points are switched. Crossover does not affect the action of a classifier. Thereafter, the GA performs mutation with a certain probability on each classifier. For each symbol of the classifier's condition, mutation switches it with a certain probability to a random value. But it never affects the condition in a way that the classifier would not match the current input anymore. Mutations also occur on the action part of a classifier. For a detailed description of the mutation

operation see [5].

Before the offspring classifiers can be inserted into the population the GA performs a GA subsumption procedure. If one of the parents is more general than the offspring classifier, the offspring is deleted and instead the parent's numerosity is incremented. The term more general means that the parent has to have the same action as the child and at every position in the condition has the same symbol as the child or a #. For this kind of subsumption to be possible, the subsuming parent has to be sufficiently experienced and accurate. It has to have an experience higher than θ_{sub} and a prediction error smaller ε_0. In XCSJava 1.0 θ_{sub} is set to 20. The reasoning behind GA subsumption is that the subsumed offspring could not add any value to the system since everything it accomplishes is already accomplished by its highly accurate parent.

If no subsumption has been taken place, the GA inserts the offspring classifiers into the population. There is a possibility that the population is full. In this case classifiers have to be deleted to free up space for the offspring. The classifiers to be deleted are selected via fitness-dependent roulette-wheel selection. The exact procedure is described in [5].

Covering The discovery unit is not only responsible for GA execution but also provides a covering mechanism. Covering takes place if some of the possible actions are not covered by the classifiers of the match set. Then, for each missing action, a correspondent classifier containing that action and containing a random matching condition is created and added to the population and match set. If the population is full, the same deletion method is applied as mentioned previously in the GA description. The original XCS also applies a covering mechanism to deal with the case that the system gets stuck in a loop. A loop could occur for example in a maze environment if the agent is moving back and forth between two cells all the time. XCSJava 1.0 implements a simpler mechanism to deal with loops. It is incrementing a counter every step and the specific problem instance is terminated if that counter exceeds a certain threshold. The counter threshold is set to 50 in XCSJava 1.0.

2.4 Action Set Subsumption

Besides the GA subsumption described in 2.3.4 there is another kind of subsumption, called action set subsumption, taking place in XCS. The underlying principle is the same as for GA subsumption but it occurs every time an action set has been updated. Action set subsumption first identifies the most general classifier in the action set with sufficient experience and accuracy. The term 'most general' refers to the classifier with the most # symbols in its condition. Afterward, all classifiers that are subsumed by this most general classifier are removed from the action set and population and instead the most general classifier's numerosity is raised accordingly.

2.5 XCSJava 1.0

XCSJava 1.0 is a Java implementation of the XCS system by Martin V. Butz published in the year 2000. This section describes certain aspects specific to XCSJava 1.0. It explains the problem types this implementation is able to solve and briefly introduces the main flow of the program.

2.5.1 Problem Types

XCSJava 1.0 is able to solve two kinds of problems, the multiplexer problem and five distinct maze tasks. Whereas the multiplexer is a single-step problem, maze problems in general are multi-step problems.

Multiplexer Problem The multiplexer problem is defined for binary strings that are assigned either to class 0 or 1. The string of bits consists of an address part and remaining bits. The address points to a single bit in the remaining part and if that bit is 0 (resp. 1) the problem instance belongs to class 0 (resp. 1). The multiplexer can be of different sizes following the pattern: $address\ length + 2^{address\ length}$. Consider the 3-multiplexer. The binary string is of size three with the first bit constituting the address. For the 3-multiplexer 000 is classified as 0 since the zeroth bit after the address is 0. In contrast 010 belongs to class 1. Correct classifications for all instances of the 3-multiplexer are:

- '010', '011', '101', '111' belong to class 1

- '000', '001', '100', '110' belong to class 0

Common problem sizes are the 6-mulitplexer, 11-multiplexer and 20-multiplexer. XCSJava 1.0 supports multiplexer problems of any size. It just uses the largest multiplexer fitting the specified string length and fills the irrelevant extra bits with random values.

Maze Problems A maze problem consists of a grid of cells. A cell can be empty or contain food or an obstacle. A moving agent (also called animat [46]) that was placed on a random cell in the beginning, is moving around in the maze trying to find food. The animat is able to move to all eight adjacent cells of its current position. If it is moving towards an obstacle it does not leave its actual position but still one time step elapses. If it steps on a cell containing food, the food is automatically eaten and reward is received. When food was found, the specific problem instance has been completed. Afterward the food regrows instantly and the animat is placed in another random position, trying to find food again. There are five predefined maze environments that XCSJava supports. Their definitions can be found in the 'Environments' folder of the project. The mazes Woods2 and Maze4 are shown in figure 2.2. If in a maze without borders the animat is moving beyond an edge of the environment, it reappears at the opposite side. In some environments such as Woods2 there are two different kinds of obstacles and food. The animat treats them all the same but this increases the complexity of the problem.

2.6 Program Execution

XCSJava takes four to six parameters as input to control the main program execution. These parameters specify the kind of problem to be solved, the output file to document the performance and so on. For a detailed description, see the documentation [2]. When XCSJava starts, it first decodes the input parameters and instantiates the correct environment that specifies the problem to be solved. Afterward it executes the main cycle for a certain number of times that can be defined by an input parameter. Typical is a number of five to twenty thousand. When the main cycle has been executed the specified number of times, one experiment finished. XCS then might conduct an additional number of ex-

Woods2:

```
****************************
*QQF**QQF**OQF**QQG**OQG**OQF*
*OOO**QOO**OQO**OOQ**QQO**QQQ*
*OOQ**OQQ**OQQ**QQO**OOO**QQO*
****************************
****************************
*QOF**QOG**QOF**OOF**OOG**QOG*
*QQO**QOO**OOO**OQO**QQO**QOO*
*QQQ**OOO**OQO**QOQ**QOQ**OQO*
****************************
************X***************
*QOG**QOF**OOG**OQF**OOG**OOF*
*OOQ**OQQ**QQO**OQQ**QQO**OQO*
*QQO**OOO**OQO**OOQ**OQQ**QQQ*
****************************
```

Maze4:

```
OOOOOOOO
O**O**FO
OO**O**O
OO*O**OO
O******O
OO*OX**O
O****O*O
OOOOOOOO
```

Figure 2.2: The Woods2 and Maze4 maze environments.
X - exemplary animat position, F and G - food, O and Q - obstacle, * - empty cell

periments, if specified so. Thereafter it documents averages of the classification results in the output file.

Main Cycle The main cycle refers to all the steps from receiving environmental input to executing an action on the environment based on that input. Generally, there are two ways of executing the main cycle, the execution modes explore and exploit, mainly distinguished by the applied action-selection method. The applied mode of execution alternates between explore and exploit.

After reception of the input state, the system forms a match set and a prediction array. These two steps are the same in each mode of execution.

In explore mode, after match set formation and forming of the prediction array, an action is chosen randomly of all the actions that are present in the prediction array. Due to XCSJava's covering mechanism, all possible actions are present in the prediction array at all times. An action set is formed of the match set and the selected action is executed on the environment. For single-step problems, all classifiers of the current action set are updated and the GA is applied to it. For multi-step problems, both procedures are applied to the previous action set A_{-1}. The purpose of explore mode is solely to gain information and explore the problem space and not to make good decisions.

In exploit mode the action with the highest expected payoff is chosen. That is the action in the prediction array with the highest value associated to it. The GA is never active in exploit mode and the credit assignment unit is only activated in multi-step problems. The concern of exploit mode is to maximize the system's reward. In this mode the system keeps track of its performance to determine how accurately it is classifying.

Whereas in the original XCS and in [5], the mode of execution is chosen randomly (with probability 0.5 each), XCSJava 1.0 simply alternates between explore and exploit.

Chapter 3

XCS-DR

This chapter introduces the agent-based extension of XCS, XCS-DR. XCS-DR stands for 'XCS with Distributed Rules'. First, the main enhancements and all of its consequences to the overall system are explained. XCS-DR is mostly distinguished from traditional LCS by the structure of its classifier population. In XCS-DR the population is not just a mere pool of classifiers but is subdivided into several agents of a certain size, all of them containing classifiers. The agents are able to exchange or delegate the input state to be classified. This increase in the population's complexity implies consequences to all other components as well. This chapter provides a coherent picture of all the adapted components and procedures taking place inside XCS-DR. First, it is explained XCS-DR's architecture and all of its adapted components. The subsequent section describes the main execution cycle. Thereafter, it is shown how XCS-DR behaves in exploit mode. In the ensuing section, explore mode is introduced and the challenges the agent-based architecture posed to it. Finally, there is a section discussing the limitations of XCS-DR since many original ideas and possible enhancements could not be incorporated into its current design. In many cases are pseudo-code algorithms displayed to facilitate a better understanding of XCS-DR's inner workings.

Note that the term agent might be a bit confusing in this context as the notion of an agent in this thesis differs from the definition of a traditional software-agent. The term has been adopted from [40].

From now on, when it is referred to the 'original XCS' or 'original system', the XCS implemented by XCSJava 1.0 is meant.

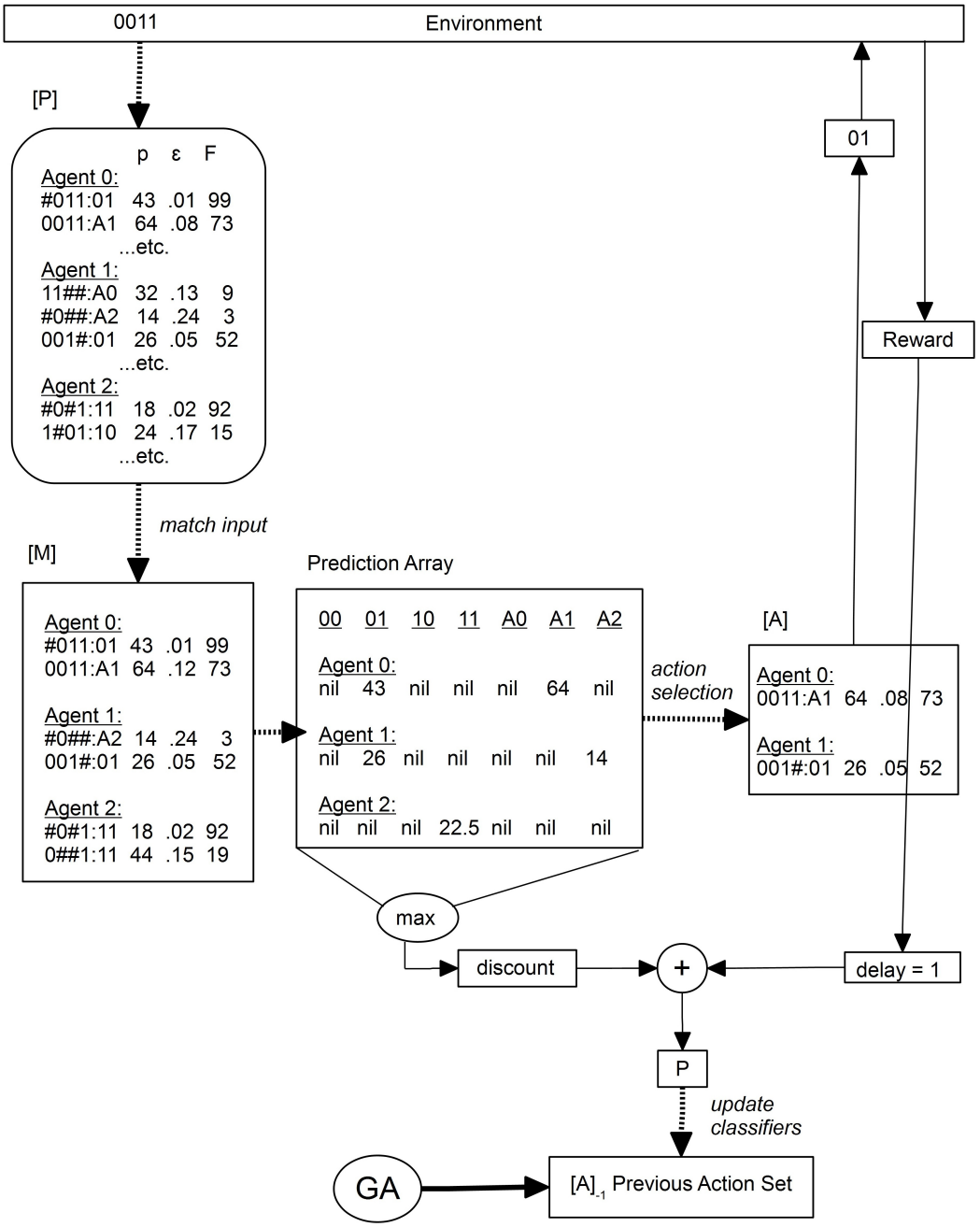


Figure 3.1: Basic components of XCS-DR. Actions beginning with an 'A' mark delegations and thus represent the ID of the target agent (i.e. 'A0' marking a reference to $Agent_0$).

3.1 Structure of XCS-DR

Figure 3.1 presents an overview of XCS-DR's components and how they interact. Since XCS-DR is still a XCS it consists of the same parts as the original system

but partially, their inner workings differ vastly from the archetype. As can be seen in figure 3.1 all the classifier sets as well as the prediction array are subdivided into agents. Also the possible actions a classifier can propose are not just actions on the environment but also delegations to other agents. In the latter, case the input state is handed to the referenced agent. The focal points, that separate XCS-DR's architecture from the original, are the set of possible actions, the structure of the classifier sets and prediction array and the way they are formed in certain situations. Also the functionality of the reinforcement component is adapted extensively.

3.2 Components of XCS-DR

As noted earlier XCS-DR includes the same components as the original XCS. This section provides an overview of the design of every particular component and points out the differences to the original.

3.2.1 The Classifier

The classifier in XCS-DR is basically composed of the same elements as in the original system. Only the action part is enhanced. Every classifier either contains a traditional action that is being executed on the environment or the action part can be the ID of an agent. The latter denotes that the classifier's action proposes a delegation of the input state to the referenced agent. Therefore, for k agents and n environmental actions we have $A \in \{a_1, a_2, \ldots, a_n, Agent_0, Agent_1, \ldots, Agent_{k-1}\}$. From now on, actions that contain a delegation are referred to as delegation actions whereas traditional actions are referred to as classification actions. Classifiers containing a delegation action are simply referred to as delegations and classifiers containing a classification action are referred to as classifications. The agent that a delegation points to is called target agent.

3.2.2 Performance Component

The Population As mentioned earlier the main enhancement of XCS-DR lies in the partitioning of the population. XCS-DR's population is subdivided into agents with each agent having a unique ID assigned to it. For k agents the ID

Algorithm 3.1 Form Match Set

```
1: procedure FormMatchSet(state)
2:     Initialize [M] with empty agents
3:     AddMatchingClassifiers(state, entryAgentID)
4:     while possible action missing in [M] do
5:         PerformCovering(missingAction)
6:     end while
7: end procedure
```

consists of the word *'Agent'* linked to a number from 0 to $k-1$ resulting in the possible IDs $Agent_0$, $Agent_1, \ldots,$ $Agent_{k-1}$. Each agent holds a set of distinct macro-classifiers. For the agents there is a *slot number* s specified, that defines the maximum number of classifiers (not macro-classifiers) to be held by a single agent. When the input state from the environment arrives at the population it is handed to an entry-agent to match the input. The entry-agent is either always the same or it is selected randomly each time.

The Match Set Since the population is subdivided into agents this structure is required for the match set as well. A matching classifier of $Agent_i$ of the population will be inserted into $Agent_i$ of the match set. To begin with the matching process, there needs to be an entry point in the population to start at. This so-called entry-agent can either be fixed or random. This does not affect match set formation. The match set formation procedure is the same for each mode of execution. To match the classifiers of the population a kind of depth-first search is performed. The classifiers in an agent are examined one after another and each matching classifier is added to the according agent of the match set. If a matching classifier contains a delegation action, it is added and thereafter the delegation is followed and the matching procedure continues recursively in the target agent. This happens only if the target agent has not yet been visited. After a delegation has been fully explored, the matching procedure continues in the originating agent. This depth-first search is achieved by the recursive function AddMatchingClassifiers described in algorithm 3.2. Algorithm 3.1 describes the whole match set formation. If, after the recursive matching process, there are still possible actions missing in the match set, the covering mechanism occurs. See section 3.2.4 for a detailed explanation of the covering process.

Algorithm 3.2 Add Matching Classifiers

```
1: procedure AddMatchingClassifiers(state, agentID)
2:     if agent with agentID already matched then
3:         return
4:     end if
5:     currentAgent ← agent of [P] with agentID
6:     for all classifier of currentAgent do
7:         if classifier matches state then
8:             add classifier to according agent of [M]
9:             if classifier.action is delegation action then
10:                AddMatchingClassifiers(state, classifier.action)
11:            end if
12:        end if
13:    end for
14: end procedure
```

The Prediction Array As displayed by figure 3.1, the prediction array also follows the agent structure. Hence, for each agent in the match set there is an according agent in the prediction array. In XCS-DR the values of a single prediction agent are computed in the same way as the whole prediction array in the original XCS. The basis for calculating the prediction values of a prediction agent are the classifiers of the according match set agent and not the whole match set. Thus, to compute the values of $Agent_i$ of the prediction array, XCS-DR takes all classifiers of $Agent_i$ of the match set into account. The precise computational step undertaken to calculate each entry of a prediction agent is displayed by formula 3.1 in the previous chapter. All agents in the prediction array are completely independent of each other.

Naturally, has every prediction agent an additional entry for each delegation action. The prediction values of delegation actions are calculated just as for classification actions.

The Action Set The action set is of the exact same structure as the match set, but contains only a subset of the match set's classifiers. There are several distinct ways to form an action set, each one being associated with a certain mode of execution. These procedures will be introduced when their corresponding modes of execution are discussed.

3.2.3 Reinforcement Component

Updating classifiers and distributing payoff differs from the original system. There are commonalities, such as the update order of the parameters *experience*, *prediction*, *prediction error, action set size* and *fitness.* Also the updates occur as well on the previous action set $[A]_{-1}$ in multi-step problems respectively on the current action set $[A]$ in single-step problems. As in the original system, in single-step problems the updates only occur during explore and in multi-step problems the updates occur during both explore and exploit. Generally, action sets are updated in XCS-DR by iterating over all of their agents and updating all the classifiers of an agent one after another. The update procedure of the parameters *experience* and *action set size* did not change compared to the original. The updates of *prediction*, *prediction error* and *fitness* are dependent on whether the current classifier is a delegation or classification and the current mode of execution. These procedures will be examined later on when the corresponding execution modes are introduced.

Fitness Decline The agent-based architecture of XCS-DR is posing some problems to the fitness calculation. Simply applying the original fitness update procedure lead to unsatisfying results. XCS-DR still applies the original Widrow-Hoff formula for the fitness update. But the relative accuracy is calculated differently in some cases. Consider classifier cl_j and recall formula 3.3 for the fitness update:

$$F_j \leftarrow F_j + \beta \left(k_j^{'} - F_j \right)$$

with the relative accuracy $k_j^{'}$:

$$k_j^{'} = \frac{n_j * k_j}{\sum_{i=1}^{s} n_i * k_i} \tag{2.1}$$

Assume cl_j is a high fitness classifier of one agent and the other agents do not contain copies of it. Further more, assume that the traditional fitness calculation formula were applied. If a copy of cl_j appeared in an arbitrary agent, due to the GA replicating and inserting that classifier, a decline of the fitness values of both copies would occur. This is because the reinforcement component of XCS-DR updates every macro-classifier of every agent separately.

As explained earlier and displayed by the formula, the fitness of cl_j is de-

termined by computing its relative accuracy in the action set. This results in much lower fitness values if several instances of cl_j are scattered across multiple agents. This is because all the scattered copies of cl_j are updated independently, but add collectively to the accuracy sum. Since every instance of cl_j has a lower numerosity than they have altogether, for each scattered instance of cl_j, the numerator of equation 2.1 is much smaller than it would be if all classifiers were stored in the same agent. This leads to a much lower relative accuracy. Hence, the scattered cl_j share their total fitness, proportionate to their respective numerosity. If a classifier appears multiple times with almost equal numerosities in every location, the resulting fitness value declines significantly. The more scattered a classifier is and the higher its accuracy, the stronger is the resulting total fitness decline.

Two strategies have been applied to avoid this effect, one for classifications and another one for delegations. The former is explained in section 3.2.4 and the latter in 3.5.8.

Overgenerals The reinforcement component of XCS-DR has been slightly modified to contribute to the evolution of more accurate classifications. During early experiments, the system exposed a tendency towards evolving overgeneral classifiers. Overgenerals are classifiers whose condition is too general and thus matches too many environmental states. This leads to the misclassification of some problem instances. The design of the original XCS prevents overgenerals from emerging but for some reason such classifiers appear in XCS-DR. This indicates that the system's components are not yet working perfectly to evolve maximally accurate and general solutions, as XCS does. The most devastating effect in XCS-DR was exhibited by classifications containing only dont-care symbols in their condition part. Such a classification must be an overgeneral, since none of the problems implemented by XCS-DR can be solved by one single, maximally general classifier. A problem that could be solved by a single classifier with a maximally general condition would not be of any practical value.

Hence, a very simple step has been implemented to prevent such overgeneral classifiers from causing any damage. During the fitness update of classifications it is checked whether or not their condition contains dont-care symbols only. If so, the following Widrow-Hoff formula is applied for the fitness update:

Algorithm 3.3 Covering

```
1: procedure PerformCovering(missingAction)
2:     cl_cover ← generate covering classifier with missingAction
3:     insert cl_cover into random agent of [M]
4:     insert cl_cover into same agent of [P]
5:     if missingAction is delegation action then
6:         AddMatchingClassifiers(state, missingAction)
7:     end if
8: end procedure
```

$$F_j \leftarrow F_j + \beta \left(\frac{k'_j}{100} - F_j \right)$$

The relative accuracy is divided by 100. This tweak resulted in a decline of such overgenerals and vastly improved the system's accuracy. However, it just alleviates the symptoms, but not the cause. Unfortunately, it could not be figured out why these overgenerals appear and how to prevent their emergence in the first place. Note that this strategy is only applied to classifications and not to delegations. Applying it to delegations did not have much of an effect.

3.2.4 Discovery Unit

Covering XCS-DR's covering mechanism is adapted to fit the enhanced needs of the system. Covering is invoked if there are actions missing in the match set. An action is missing if it is not present in any of the agent's classifiers of the match set. This also includes delegations. Assume no classifier in the match set delegates to $Agent_i$, then at first a random matching classifier containing the delegation action '$Agent_i$' is created. This covering classifier is inserted into a random agent of the match set. If the chosen agent has no free slots, one classifier is deleted. This process is the same for classification actions. If the covered action is a delegation, the system visits the newly covered target agent after the insertion of the delegation and adds all of its matching classifiers to the match set as well. After that, the system checks again for missing classifiers. This cycle repeats until there are no missing actions left. Thus, this covering mechanism ensures that the input state is always compared to all agents of the population. Algorithm 3.3 depicts this process in pseudo-code.

Algorithm 3.4 Genetic Algorithm Insertion

```
1: procedure InsertIntoPopulation(classifier)
2:     if classifier is classification AND classifier already present in [P] then
3:         insert classifier into agent of [P] where copy exists
4:     else if classifier is delegation then
5:         insertAgent ← random agent that is not target agent of classifier
6:         insert classifier into insertAgent of [P]
7:     else
8:         insert classifier into random agent of [P]
9:     end if
10: end procedure
```

Genetic Algorithm The GA of XCS-DR is extended to evolve delegations as well. It acts on action sets that either contain classifications only or delegations only or both classifications and delegations. It applies the same roulette wheel selection to select classifiers for replication as the original, with the only difference that it is applied across all agents. Crossover and mutation of the selected classifiers operate identical to the original system with the exception that the possible mutations of an action also include all delegation actions. The GA subsumption procedure is the same as in the original. It is acting across all action set agents but applies the same steps as XCSJava 1.0. The biggest difference of XCS-DR's GA can be found in the insertion of the offspring classifiers. While it did not matter how to insert a classifier in the original XCS it does make a big difference in what agent to insert a classifier in XCS-DR. Algorithm 3.4 illustrates the whole insertion process.

For reliable delegations it is desired that they are wide-spread. If one agent handles certain input very well, all the other agents should know that it is best to delegate this kind of input to it. Therefore delegations are always inserted into random agents but a delegation is never inserted into the agent that it is pointing to. In the special case that XCS-DR defines only one agent, all delegations are inserted into that agent. This special case is not considered in the pseudo-code algorithm 3.4 to preserve clarity.

For classifications however, it is not desired that they spread across several agents. A classification is a piece of knowledge about the environment. The agents are supposed to subdivide the problem space. There is no need for them to share their knowledge since that would make delegations obsolete to a certain

Algorithm 3.5 Main Loop

```
1:  procedure MainLoop
2:      repeat
3:          state ← receive state from environment
4:          [M] ← FormMatchSet(state, entryAgentID)
5:          PA ← generate prediction array from [M]
6:          winningAction ← select action using PA
7:          [A] ← form action set
8:          reward ← execute winningAction on environment

9:          if [A]_{-1} is not empty then
10:             update [A]_{-1} with reward
11:             invoke GA on [A]_{-1}
12:         end if

13:         if problem solved then
14:             updated [A] with reward
15:             invoke GA on [A]
16:             empty [A]_{-1}
17:         else
18:             [A]_{-1} ← [A]
19:         end if
20:     until specified number of problem instances solved
21: end procedure
```

degree. Therefore, if an offspring classification that is already existent in the population, has to be inserted into the population, it is always inserted into the agent where the identical copy is present. If the offspring is not yet existent in the population, it is inserted into a random agent. This procedure ensures that there are no identical classifications in multiple agents and thus avoids the aforementioned fitness decline a priori. Hence, classifications can be updated using the original formula 3.3.

3.3 The Main Loop

Algorithm 3.5 displays the main operation cycle of the program in a multi-step environment. In the beginning the current state is received from the environment. Next, a match set is formed and a prediction array created. Thereafter an action selection method is used to obtain the winning action. Which action

selection scheme is used depends on the current mode of execution. Then the winning action is executed and the reward received (these steps are performed identically in single-step environments). The next step is to update the previous action set and run the GA on it (in a single-step environment updates and the GA occur only on the current action set). If the system is in exploit, the previous action set is only updated but the GA does not occur (in a single-step environment no GA and updates occur during exploit). If the environment suggests that the particular problem instance is solved (e.g. resources are reached by a robot) the system also updates the current action set using the received reward and runs the GA on it. Further more it empties the previous action set because the next environmental input will present a new problem instance that is unrelated to the previous one. If the environment suggests that the particular problem instance has not been solved, the previous action set is assigned the current action set. This cycle repeats until the specified number of problem instances has been solved.

3.4 Exploit Mode

There are two different modes of execution in the original XCS, explore and exploit. The mode the system is in affects the action selection method, reinforcement component invocation and GA invocation. While the differences between both modes in the original XCS are pretty limited, in XCS-DR explore mode is much more complex and differs in several major ways from exploit. This is due to the additional need to evolve good delegations. However, exploit mode is similar to the one applied by the original system. This section describes how XCS-DR executes action selection, action set formation and classifier updates in exploit mode. The match set and prediction array formation are the same in each mode.

3.4.1 Action Selection

Action selection is more complex in XCS-DR than in the original system. This paragraph describes the best action selection scheme used in exploit mode. Since there is another best action selection scheme introduced later, it is named best action selection exploit. Best action selection exploit is more extensive than

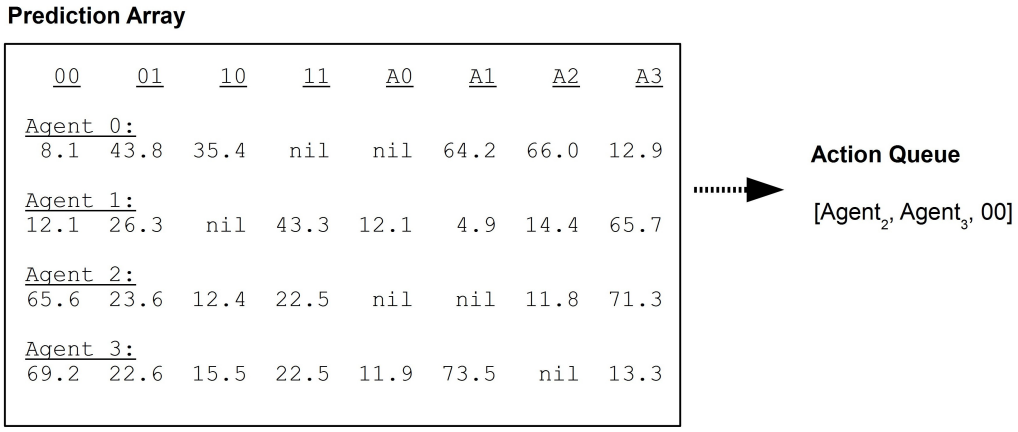


Figure 3.2: Examplary best action selection exploit. $Agent_0$ is the entry-agent. The selection procedure leads to the selection of the delegations to $Agent_2$ and $Agent_3$. In $Agent_3$ the delegation to $Agent_1$ is the best action. But that would introduce a cycle and therefore the second best action '00' is chosen.

best action selection in the original system and generally selects more than one action. In XCS-DR the best action of each prediction agent is considered, beginning with the entry-agent. First the entry-agent of the prediction array is examined and the action with the highest expected payoff is added to an action queue. In case this is a classification, the queue is returned immediately. However, if the best action is a delegation, the system follows that delegation, selects the best action from the target agent and adds it to the queue as well. This process continues until the added action is of the type classification. Then the action queue consisting of several delegations with a classification action on top is returned.

For this process to work, the system needs to be able to detect delegation cycles. Whenever a delegation leads to an agent already examined, the next best action is chosen. If all possible actions of a prediction agent lead to a cycle, the system takes a step back to the previous agent. Due to covering it is ensured that there are always some classifications in the match set and it is impossible to not find a classification action. Figure 3.2 provides an example of best action selection exploit.

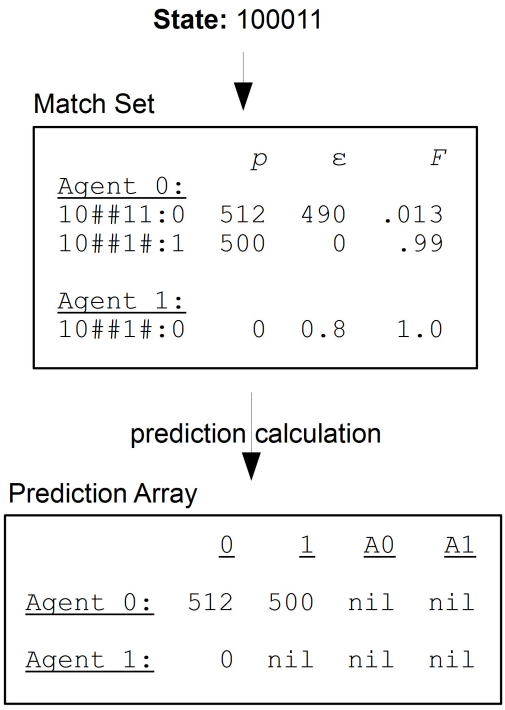


Figure 3.3: Example of malicious prediction calculation. The highest prediction of $Agent_0$ is calculated for action 0 which is wrong.

3.4.2 The Prediction Array Problem

In a prediction array subdivided into several agents, sometimes occurs a deceiving misrepresentation of the prediction values of classification actions. This is due to the design decision that identical classifications are always inserted into the same agent. Thus, high quality classifiers that would have usually neutralized very inaccurate classifiers are often contained in the wrong agent. This leads to malicious predictions in some instances when computing the prediction array. Consider the example presented in Figure 3.3. It shows a possible match set and prediction array for the problem instance 100011 of the 6-mulitplexer problem. As you can see the prediction array assigns the highest prediction to action 0 in $Agent_0$ although this is the wrong action and the correct classifier is part of the same agent set as well. Altough the first classifier of $Agent_0$ has a fitness of only 0.013 and a *prediction error* as high as 490, it still prevails. If all classifiers were part of a traditional non-agent-based match set, that very low quality classifier would have been neutralized by the high quality classifier in $Agent_1$ that expects zero payoff for taking action 0. If both classifiers were part

of the same agent or part of a traditional match set, their combined prediction for action 0 would have been $\frac{512*0.013+0*1.0}{1.0+0.013} = 6.571$ which is far below the actual 512 for the same action in $Agent_0$. Due to the fact that the neutralizing classification is part of $Agent_1$ and all identical classifications will be inserted into $Agent_1$ as well, this one has no chance to influence the prediction calculation of $Agent_0$. This structural difference to the original system enables low fitness classifiers, that would have been irrelevant in a non-agent-based approach, to gain control in some cases and lead to wrong classifications.

The straightforward solution applied by XCS-DR to restrict the influence of such malicious classifiers is to ignore classifiers with too low of a fitness value. During calculation of the prediction array there has to be found a sensible fitness threshold that excludes very weak classifiers. The fitness of each newly created classifier is initialized with 0.01 and experiments have shown that setting this value as a threshold for the prediction calculation leads to good results. This means the prediction array ignores every classifier with a fitness below 0.01 in its prediction calculation procedure. The threshold should not be too high since that causes good classifiers to be ignored too often as well. The exclusion of low fitness classifiers takes place during prediction calculation only. These classifiers are still part of the action set and get updated as every other classifier.

3.4.3 Formation of the Action Set

After applying best action selection exploit, an action set is formed. Action selection exploit does not necessarily return only a single classification action but might instead result in a queue of several delegations and a classification action on top. Due to the particular process of choosing the best action of every prediction agent beginning with the entry-agent, each action in the queue can be associated with a certain match set agent. The action that first entered the queue is the one selected from the entry-agent. Therefore all classifiers in the entry-agent of the match set containing that first action are added to the according agent of the action set. If the added action is a classification action, the queue does not contain any additional actions and the action set is complete. If it is a delegation, its target agent of the match set is investigated for classifiers containing the next action in the queue. This process is repeated until every action in the queue was considered. Algorithm 3.6 depicts this process.

Algorithm 3.6 Action Set Formation in Exploit

```
1: procedure FormActionSet(actionQueue, entryAgentID)
2:     currentAgentID ← entryAgentID
3:     for all action of actionQueue do
4:         matchSetAgent ← agent of [M] with currentAgentID
5:         for all classifier of matchSetAgent containing action do
6:             add classifier to agent with currentAgentID of [A]
7:         end for
8:         if action is delegation then
9:             currentAgentID ← action
10:        end if
11:    end for
12: end procedure
```

3.4.4 Updating Classifiers

As noted earlier, parameter updates occur only during multi-step problems in exploit. The update procedure iterates over all agents of the action set, updating each classifier at a time. The *prediction* and *prediction error* update procedure applies during exploit the identical MAM technique applied by XCSJava 1.0 and there is no distinction between classifications and delegations. The maximum prediction value required to update *prediction* and *prediction error* is obtained by iterating over all prediction agents of the prediction array and returning the maximum prediction value of all classifications. It turned out that this value produces better results than using the maximum prediction of all classifications and delegations.

Calculating the fitness update value is identical to the original, only adapted to the agent structure. The accuracy sum required for the relative accuracy computation is obtained by adding up the accuracies of every classifier of every action set agent. With that value the fitness is updated using the original formula 3.3. The aforementioned fitness decline is not taking place during exploit. Due to the structure of the action set, there can not be multiple, identical classifiers in it. Each action set contains only a single classification and all the delegations are different ones because the action set is created by avoiding delegation cycles. Without identical classifiers scattered over multiple agents, no fitness decline is taking place.

All other parameters are updated just as in the original. See algorithm 3.7

Algorithm 3.7 Updating the Action Set

```
1: procedure UpdateExploit(actionSet)
2:     accuracySum ← compute and add accuracy of each classifier of
   actionSet
3:     for all agent of actionSet do
4:         for all classifier of agent do
5:             increment experience of classifier
6:             update prediction error of classifier
7:             update prediction of classifier
8:             update action set size of classifier
9:             update fitness of classifier using accuracySum
10:        end for
11:    end for
12: end procedure
```

for an overview of the update procedure.

3.5 Explore in XCS-DR

A major challenge of developing XCS-DR has been to figure out how to adapt the explore procedure to evolve working delegations. This section describes the whole explore process of XCS-DR in detail. First, it is described the way XCS-DR explores the problem space and evolves sensible classifications. Second, explore mode and delegations are scrutinized. Exploring working delegations is vastly different from exploring classifications. Several strategies are introduced and discussed. How these strategies behave in practice, when facing actual problems and what results they are producing is illustrated in detail in chapter 5.

3.5.1 Traditional Explore and Delegations

In an early stage, possibilities to evolve delegations in parallel with classifications have been investigated. This resulted in a combined explore for classifications and delegations. An approach that basically executed the classification explore procedure, but tried to incorporate the evolution of delegations into it. Therefore, a match set has been created that contained all matching classifications and delegations. In the next step the prediction array has been formed and

a random classification action selected for execution. This step is crucial for exploring classifications and therefore the action selection method could not be changed. Afterward, the action set was created by adding all classifications with the according action and all delegations that reach a classification that is already part of the action set. The term 'reaches' means that either the target agent of the delegation contains such a classification or that, by following further delegations, at least one visited agent contains such a classification. After creating the action set the selected action was executed and payoff received and distributed.

While this works perfectly fine to update classifications with the received payoff, the same procedure does not apply well to delegations. The main problem is that random action selection is not suitable to evolve delegations. That fact stems from the inherent difference between what is a valuable classification and a valuable delegation. A valuable classification correctly predicts the payoff that is received when executing its proposed action. A valuable delegation predicts the payoff that is received when the delegation's target agent executes the action with the highest prediction. These characteristics of valuable classifications and delegations directly result from the way the exploit procedure has been designed.

Since a delegation predicts payoff in a more indirect way, one can not evolve it efficiently by using random action selection. Assume, in the just mentioned explore scheme, action a_1 had been chosen by random action selection. Further more, assume there is a best action a_2 in that situation. For a delegation it does not matter what amount of payoff a_1 receives. It matters whether its target agent would have executed a_2 in exploit. And if so, the amount of payoff received by a_2 is of importance to that delegation. Hence, updating delegations with the irrelevant payoff information gained by executing a_1 is completely misleading. In practice, updating delegations with such bad information led to the evolution of delegations with extremely high prediction errors and very low fitnesses. To avoid this issue a separate delegation explore mode has been added to the system.

Note that I do not consider it impossible to evolve useful classifications and delegations in parallel. But all the investigated approaches led to very inaccurate delegations and evolving delegations separately seemed to be the more promising approach.

3.5.2 Exploring Classifications

Since no reasonable way to evolve delegations and classifications in parallel could be found, both tasks have to be achieved independently from each other. Hence the traditional explore mode had to be split in two explores. The system no longer alternates between exploit and explore but between exploit, classification explore and delegation explore. Pursuing this approach takes more time to evolve good classifiers since in total twice as many explore steps are performed compared to the original XCS. To evolve good classifications during explore, XCS-DR mainly proceeds as the original. This is the mode called classification explore. For a given state, a match set is created, covering might occur, a random action is chosen, an action set is built and the reward is collected. With the received reward all classifiers of the previous action set are updated and the GA might occur. The match set is formed as described earlier. An action is chosen randomly from the set of possible classification actions. The action set is created by adding all classifiers of the match set to it that hold the winning classification action. The delegations of the match set are ignored. The update procedure is the same that is applied during exploit. The fitness decline can not occur because only classifications are part of the action set and identical classifications are always added to the same agent. Thus, no classifiers are scattered across the action set.

Due to the discovery unit inserting identical classifications always in the same agent, every agent is able to solve only parts of the problem. The general process of evolving classifications is so close to the original that for a given environment the same classifiers prevail in XCS-DR as in the original system. That is desired behavior since the original system explores an accurate and maximally general solution for a given problem. See chapter 5 for an experimental comparison of a single-agent XCS-DR and XCSJava 1.0.

3.5.3 Evolution of Delegation Classifiers

As noted earlier it is the goal of a single delegation to point to an agent more suitable for matching input states. This means, if the matching input state were classified by the home agent of the delegation, less payoff would be received than if the input were classified by the delegation's target agent. Thus the main goal of a delegation explore mode must be to distribute payoff in a way that

Algorithm 3.8 Best Action Selection Explore

```
1: procedure BestActionSelectionExplore(predictionArray)
2:     bestAction ← null
3:     maxPrediction ← −1
4:     for all prediction agents do
5:         for all action of possible classification actions do
6:             currentPrediction ← value of action in current prediction agent
7:             if currentPrediction > maxPrediction then
8:                 maxPrediction ← currentPrediction
9:                 bestAction ← action
10:            end if
11:        end for
12:    end for
13:    return bestAction
14: end procedure
```

delegations are rewarded if their target agent classifies matching input better than their home agent and to punish them, if otherwise.

The basic principle of this approach is to work with the presumably best classification action for a given state. After a certain amount of classification explore steps, one can pretty reliably determine the correct classification. The applied best action selection scheme is rather simple, comparing the prediction values of all classification actions of all prediction agents and selecting the action with the highest prediction. It is named best action selection explore and illustrated in Algorithm 3.8. All steps in delegation explore are performed in the same order as in the other modes of execution, as it was illustrated in the section The Main Loop. The classifications that are part of a match set are completely ignored in this mode. Up next are discussed four particular strategies for realizing a delegation explore mode. These approaches mainly differ in how the action set is formed and how many delegations are included in a single action set. The update procedure is described afterward.

Delegation explore applies the standard GA that is used also by exploit and classification explore. Chapter 5 provides a performance comparison of all the introduced strategies.

Algorithm 3.9 Simple Best Action Selection Explore

```
1: procedure BestActionSelectionExploreSimple
2:     agentID ← ID of random agent of [M]
3:     actionList ← actions of according prediction agent ordered by prediction
4:     return first classification of actionList
5: end procedure
```

3.5.4 Local Best Action, Random Target Agent

This approach is standing out a little bit compared to the other strategies insofar as it applies an even simpler action selection scheme than best action selection explore. First, of course a match set is created for the input state. Thereafter the prediction array is computed and a random agent of the match set is selected. From this random agent, the best action is chosen locally by examining its according prediction agent. Thus, in this case the action selection procedure omits examining all agents of the prediction array. See Algorithm 3.9 for a description in pseudo-code. The action set is created by including all delegations from the match set that point to the previously selected random agent. After that the selected action is executed and the reinforcement component distributes the received payoff.

3.5.5 Global Best Action, All Delegations

Again a standard match set is created. The action is selected by best action selection explore. Best action selection explore is being applied and all delegations of the match set are added to the action set. Hence, the reinforcement component updates all matching delegations at once.

3.5.6 Global Best Action, Random Target Agent

The last two approaches to realize a delegation explore procedure are pretty similar. The match set formation is standard and best action selection explore is applied. In 'Global Best Action, Random Target Agent' the action set is created by choosing a random target agent and including all delegations of the match set that point to that target agent. Hence, all delegations pointing to one specific agent are updated at the same time.

3.5.7 Global Best Action, Random Home Agent

In this approach the randomly chosen agent is not marking the target agent, but the home agent. The difference to the previous approach is that the action set is created by adding to it all delegations of that random match set home agent. It does not matter where the delegations are pointing to. Therefore, in this case all delegations contained in a single random match set agent are updated at once.

3.5.8 Classifier Updates in Delegation Explore

As noted earlier, there is a difference between useful classifications and useful delegations that requires an adapted update procedure for delegations. In all previously introduced delegation explore procedures, there has been employed some kind of best action selection. Therefore, the received reward is expected to be higher than by executing random actions and it can not be used directly to update delegations. In XCS-DR a delegation receives payoff, if the prediction of the delegation's target agent is higher than the prediction of the delegation's home agent for the selected action. Otherwise, the reward for that delegation is set to zero. The idea behind this approach is that a higher prediction for the presumably best action in a specific agent indicates that this agent would rather likely select that action during exploit. Hence, if that agent is the delegation's target agent, the delegation itself is useful. Whereas the computation of P is different, the actual update formulas applied to the *prediction* and *prediction error* parameters are the ones used in the original. See Algorithm 3.10 for an illustration of this process in pseudo-code.

The fitness calculation of delegations also differs from the original. Due to the previously mentioned possible fitness decline caused by scattered delegations, a different calculation of the relative accuracy has to be applied. For a delegation d_j in the action set, there is a *total numerosity* n_{jtotal} computed by adding up the numerosities of all delegations identical to d_j in the action set. Thereafter, the relative accuracy of d_j is calculated using its corresponding n_{jtotal} instead of the actual numerosity n_j. If there are no identical delegations scattered over multiple agents, the *total numerosity* of a delegation and its actual numerosity are the same. For a delegation d_j with accuracy k_j and corresponding total numerosity n_{jtotal} is the relative accuracy computed with the following formula:

Algorithm 3.10 Updating a Single Delegation

```
1: procedure UpdateDelegation(delegation, selectedAction, reward)
2:     homePrediction ← prediction of selectedAction in home agent of
   [7] delegation
3:     targetPrediction ← prediction of selectedAction in target agent of
   [7] delegation
4:     if homePrediction < targetPrediction then
5:         P ← reward + γ * maxPrediction
6:     else
7:         P ← 0 + γ * maxPrediction
8:     end if
9:     update predicton and prediction error of delegation using P
10: end procedure
```

$$k_j^{'} = \frac{n_{jtotal} * k_j}{\sum_{i=1}^{s} n_i * k_i}$$

The resulting relative accuracy is applied to the traditional Widrow-Hoff formula for the fitness update. Unfortunately, in some cases the resulting F_j happens to be greater than 1.0. The cause of this effect could not be found out. In this case F_j is simply set to 1.0. This might not be the optimal fitness update procedure but it is yielding much better results than other tested procedures such as updating delegations agent-wise.

3.6 Limitations and Conclusions

Originally have been considered a couple of concepts and ideas that did not make it to the final version of XCS-DR. For most parts, this was due to the agent structure increasing the system's inherent complexity substantially. Introducing all intended features would have gone beyond the scope of this work. It would have taken too much time and development effort to realize all original ideas. The highest priority has been to get the delegations working. There is still lots of room for improvement and further adaptations and enhancements.

First and foremost, although the architecture of XCS-DR supports chains of delegations, the reinforcement component does not encourage the emergence of such structures. By chains of delegations it is meant that an input state is delegated several times from the entry-agent to the target agent, to another

target agent, and so on until it is finally classified. The reinforcement component only rewards delegations when their target agent immediately provides a high prediction value and does not provide any payoff if further delegations would have lead to successful classification instead. This simplification was necessary to evolve sensible delegations in the first place but an extension of the reinforcement component is thinkable.

Also, at first it was considered to introduce a way of penalizing delegations as it is applied in [40] to exert a certain kind of control over emerging delegation structures. For instance one could think of generally penalizing delegations by distributing less payoff to them in order to encourage early classification. Or if chains of delegations were emerging in the system one could restrict the maximum number of hops through penalties. Due to the complications of evolving valuable delegations in general, this ideas had been discarded and there is no penalty whatsoever implemented.

Another idea has been to implement graph structures for the agents. For instance, enabling a grid topology where only delegations to adjacent agents would have been allowed. It would not be difficult to implement such a predetermined graph structure but this could not go hand in hand with the way classifications are distributed among agents right now. Certain agents would not be able to delegate to the agent containing the correct classifier for a certain state because of the according agent not being adjacent in the graph. Therefore, the distribution of classifications would have to be changed, which would entail further adaptations.

Finally, the agents of XCS-DR might not be independent enough of each other to be applied successfully in a distributed scenario. The explore process requires a certain amount of communication between the agents, e.g. for calculating the accuracy sum or sharing reward which might be too much to handle efficiently in a distributed environment. However, it would certainly be possible to optimize these processes for distributed environments. As of right now, the system could easily be adapted to offline application in distributed scenarios. In offline learning a LCS is previously trained to evolve the classifier population before being applied to the actual problem. After the training phase the classifier set is fixed. Offline learning works for environments that are not changing but is inapplicable to fluctuating environments. Since the exploit mode of XCS-DR does not require lots of communication between the agents except for delegating

input, an adapted XCS-DR would be suitable for offline applications such as wireless sensor networks.

Chapter 4

XCS-DR Java Implementation

The architecture of the XCS-DR implementation is vastly different from XCSJava 1.0. While XCSJava 1.0 was the starting point, its whole design had to be revised and enhanced to adapt the system to its additional requirements. Also XCS-DR implements a new kind of problem it is able to solve, the incremental parity problem. First, in this chapter, the incremental parity problem is examined and compared to the multiplexer problem. Next, the structure of XCSJava 1.0 is discussed and criticized in brief and some of its unfavorable design decisions and implementation details are traced down. Thereafter, the overall architecture of XCS-DR's Java implementation is introduced and explained. An overview of the package and class structure is presented as well as a brief description of most classes. Further more, this chapter shows how to run and configure the XCS-DR implementation and how to read the output. Additionally, it is explained how to edit the project's source code. This is crucial to be able to fully explore XCS-DR's functionality since some parameter changes can only be undertaken in the source code.

4.1 Problem Types

XCS-DR is able to solve the multiplexer and maze problems that the original system implemented. Further more it is extended to also solve the incremental parity problem (IPP). The incremental parity problem of size m (m−IPP) is defined for binary strings of length m. Strings have to be classified by their parity. The parity of such a string is 0 if the number of 1s in the string is even and 1 otherwise. E.g. the instance 00101 of the 5-IPP is of class 0, whereas 01101

is of class 1. This characterization makes it a single-step problem that is different from the multiplexer problem insofar, as it lacks the potential for generalization. Whereas an accurate solution to the multiplexer requires relatively few rules due to most positions being irrelevant, the m-IPP requires at least $2^{(m-1)}$ [40] rules to correctly classify every problem instance. This is because every single bit of every IPP instance is relevant and it is impossible to generalize without sacrificing accuracy. The IPP was implemented mainly to compare how XCS-DR performs when facing problems that have very low generalization potential.

4.1.1 The Multiplexer Payoff Landscape

The XCSJava 1.0 implementation provides a payoff landscape for the multiplexer problem that has originally been taken from [48]. It is adopted by XCS-DR and can be applied by setting the configuration parameter *payoff-type* to 1. The payoff landscape associates different payoff values to different problem instances. It subdivides the problem space and a correct classification always receives 300 payoff more than an incorrect classification. For instance the correct, matching classifier 000### : 0 would receive 300 payoff when executed, whereas the incorrect classifier 000### : 1 would receive 0 payoff. 01#0## : 0 would receive 400 payoff and 01#0## : 1 would receive 100 payoff. Every possible address has different payoff values associated with it that are received after correct or incorrect classification. The payoffs rise in 100 point increments from the lowest address to the highest address.

4.2 Criticism of the XCSJava 1.0 Implementation

XCSJava 1.0 violates many principles of object oriented design in general and several Java best practices in particular. This resulted in source code that is hard to understand and to adapt. As stated by McConnell in [35, pp. 78] *"Managing complexity is the most important technical topic in software development"*. It is important for a program to be readable and to provide several levels of abstraction from the underlying technical implementation details by providing well structured classes and reasonable interfaces.

Unfortunately, XCSJava 1.0 is not making use of Java's ability to organize classes in a package structure. Each of the implemented classes is defined in the

default package, which is strongly discouraged by Java design guidelines. The classes of XCSJava 1.0 do not present a coherent encapsulation of functionality but rather mix all kinds of different procedures in a single class. For instance, the class *XClassifierSet* of XCSJava contains constructors for creating a population, a match set and an action set. All of these sets share some commonalities but also have distinct properties. Consequentially, it would have been much more beneficial to implement a common superclass and move the unique functionality of each of these classifier sets into a single subclass inheriting from the common superclass. *XClassifierSet* implements the data structure for all kinds of classifier sets but further more, it contains the code for running the GA and for creating output. This is too much unrelated functionality contained in a single class. Another obvious violation of best practices can be found in the *XCSConstants* class which implements all constants as non-static variables and hence the program has to instantiate *XCSConstants* to access its constants. There could be pointed out several other instances of poor class design that are omitted here. As a result of all these design decisions, the class design does not at all provide a clear mapping from the structure of the code to the actual problem domain.

Also, the design of the single methods in XCSJava 1.0 is lacking clarity. In many cases the layout is inconsistent, with parts of the code being indented correctly and others not. Some methods such as the match set constructor of *XClassifierSet* are very long and therefore hard to understand. Just as the class implementations, many methods do not provide functional cohesion and should have been split into shorter, more concise methods. Variables and indexes introduced often have confusing or meaningless names that are not speaking for themselves. A single loop index sometimes is used repeatedly in multiple loops, resulting in very confusing code (e.g. the method *confirmClassifiersInSet()* of *XClassifierSet*). More over, some methods provide a return value that is never used (e.g. *removeClassifier(XClassifier classifier)* from *XClassifierSet*).

All these disadvantageous implementation characteristics make the source code of XCSJava 1.0 complex, hard to understand and hard to change. To implement a version with extended functionality, the design had to be completely revised and the code refactored. This resulted in the package and class structure that is presented next.

4.3 Program Structure of XCS-DR

The Java implementation of XCS-DR is organized in a way that its package structure reflects the actual problem domain. As XCS-DR consists of an environment, performance component, reinforcement component and discovery unit, the implementation of XCS-DR defines the packages environment, performanceComponent, reinforcementComponent and discoveryComponent. Additionally, the package performanceComponent contains the two subpackages, classifierSets and classifier. There is also a package controller that is responsible for the overall program execution and a utils package that provides helper classes that are unrelated to XCS-DR's specific functionality. Figure 4.1 shows an overview of all packages of the XCS-DR implementation and how they are dependent on each other. The following sections briefly discuss the functionality and contained classes of each package.

The whole implementation was built upon XCSJava 1.0. Although almost every method of the original source code had been subject to change and restructuring, there are still lines of code in the XCS-DR implementation that have not been changed from XCSJava 1.0. Although most classes, as they are engineered right now, do not originate from XCSJava 1.0, Professor Butz' implementation provided the basic operations and the starting point of the development of the current application.

4.3.1 Package controller

This package contains classes that are responsible for the overall program execution. The contained class *XCS_DR* defines the *main(String[] args)* method and thus provides the entry point of the program.

XCS_DR: The entry point and central controller of the system. Initializes the specific XCS-DR instance by reading the configuration file, creating the according environment and setting up important parameters. Starts the execution of the specified environment and writes the output after execution.

Experiment Parent class of *SingleStepExperiment* and *MultiStepExperiment*. Provides an interface for the class *XCS* by defining the abstract method performExperiment that is implemented by its two subclasses.

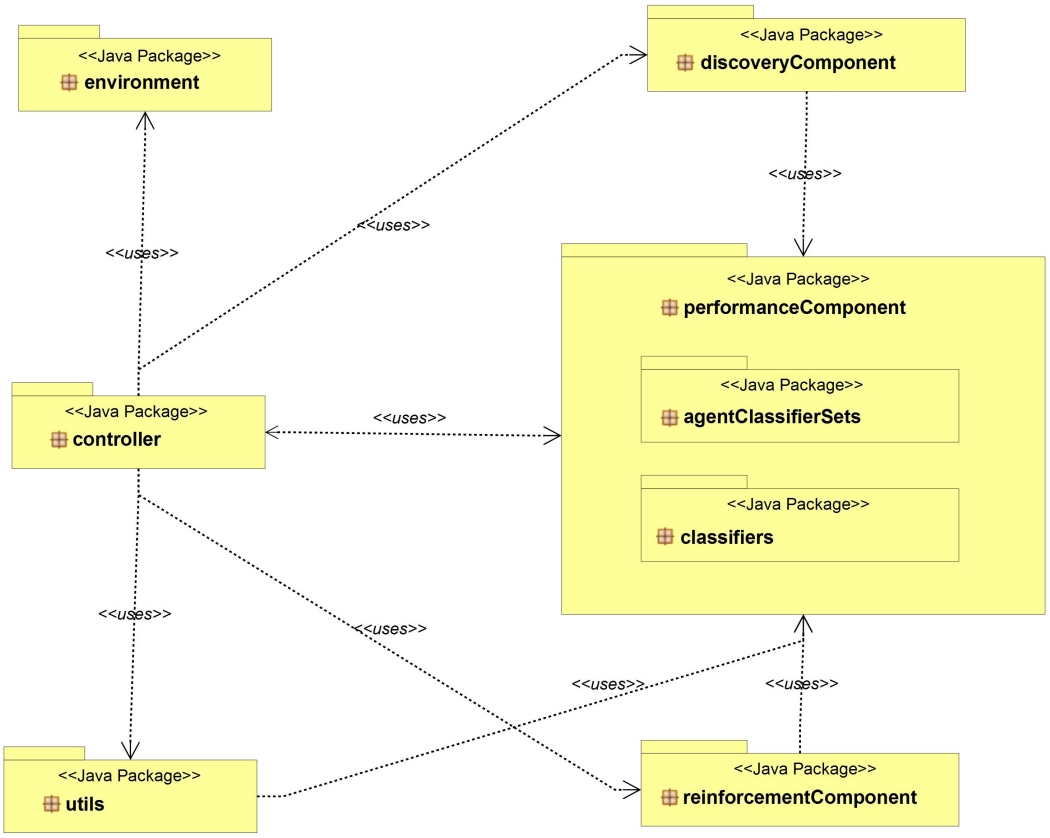


Figure 4.1: Package diagram of the XCS-DR Java implementation. All dependencies to and from subpackages of performanceComponent are illustrated as dependencies to and from their parent package.

SingleStepExperiment Controls and operates the alternation between explore classification, explore delegation and exploit in single-step environments. Interacts with the environment and invokes the reinforcement component and genetic algorithm. Collects data while solving the problem instances.

MultiStepExperiment Controls and operates the alternation between explore classification, explore delegation and exploit in multi-step environments. Interacts with the environment and invokes the reinforcement component and genetic algorithm. Collects data while solving the problem instances.

4.3.2 Package environment

This package defines all the problem types (environments) of XCS-DR. It provides an implementation of each available problem type. Further problem types could easily be added by providing additional implementations of the interface *Environment*. This package also provides a factory class for the convenient instantiating of the different environments.

Environment: Interface that defines all the methods a certain environment has to provide to XCS-DR. Important methods include *resetState()* that returns a random problem instance or *executeAction()* that executes a certain action and returns payoff.

MPEnvironment: Implementation of the interface *Environment* that represents the multiplexer problem.

MazeEnvironment: Implementation of *Environment* that represents all kinds of maze problems. Has to be supplied with a particular maze type during instantiation.

IPPEnvironment: Implementation of *Environment* that represents the incremental parity problem.

EnvironmentFactory: This factory class instantiates the correct environment during initialization. Has to be supplied with the parameters specified in the config file.

ProblemTypes: Enum that defines all problem types. Used by *EnvironmentFactory*.

4.3.3 Package performanceComponent

The package performanceComponent mainly consists of an implementation of the prediction array and contains a constants class. It includes two subpackages, classifier and classifierSets. PerformanceComponent and its subpackages contain the core part of the program by implementing the actual classifier, prediction array and all classifier sets. Figure 4.2 displays the according class diagram of this package.

AgentPredictionArray: This class represents the agent-based prediction array. It contains several instances of *PredictionAgent*, provides methods for action selection and accessing prediction values.

PredictionAgent: The class *PredictionAgent* computes the prediction values of an according match set agent. Provides methods to access the prediction values of actions. Mainly accessed by *AgentPredictionArray* during action selection.

XCSConstants: Constants class that contains all parameters that are introduced in the original system such as the learning rate β or the discount rate γ. Additionally, contains agent related constants such as the total number of agents and the number of slots per agent.

Subpackage classifier The package classifier contains classes that make up the structure of a single macro-classifier. It provides an implementation of the macro-classifier concept with all of its parameters as well as implementations of the different types of actions. Figure 4.3 displays the according class diagram of this package.

MacroClassifier: Implementation of the macro-classifier concept. This class specifies member variables for the action, condition, numerosity, prediction and all other parameters necessary to model a macro-classifier. It also provides functionality to access and set these parameters.

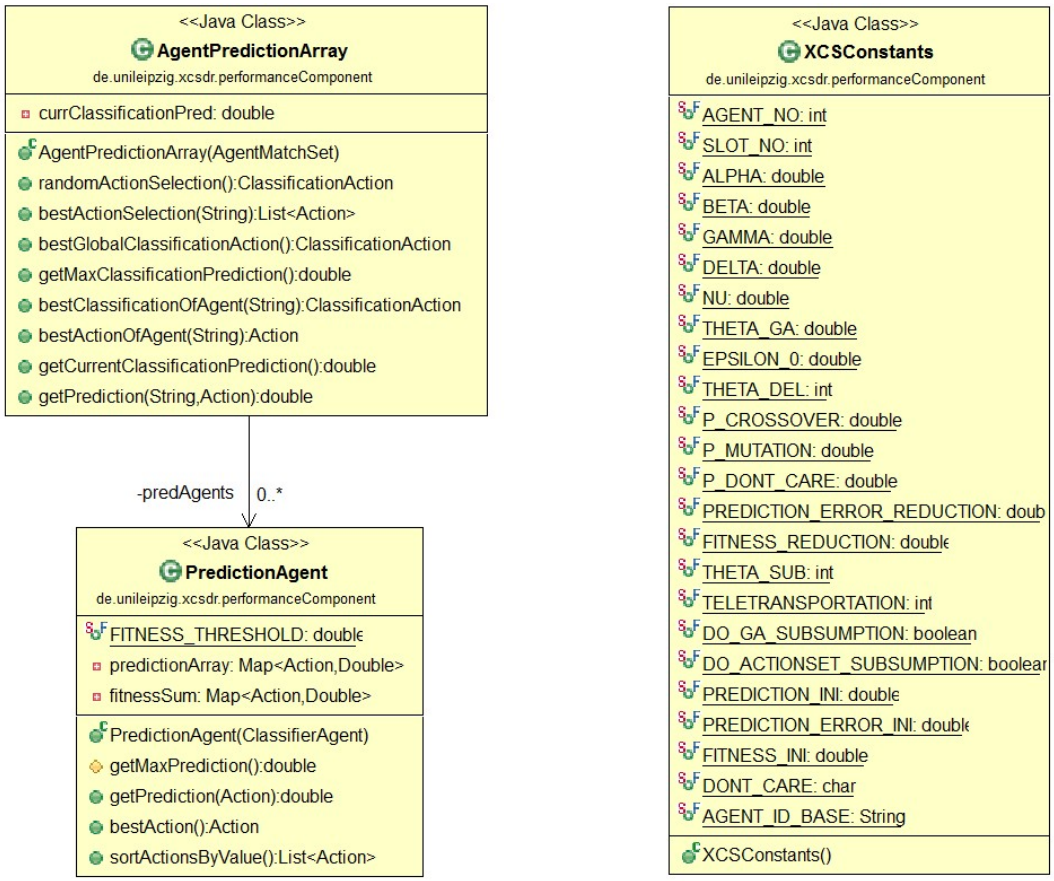


Figure 4.2: Class diagram of the package performanceComponent. Private methods are not displayed.

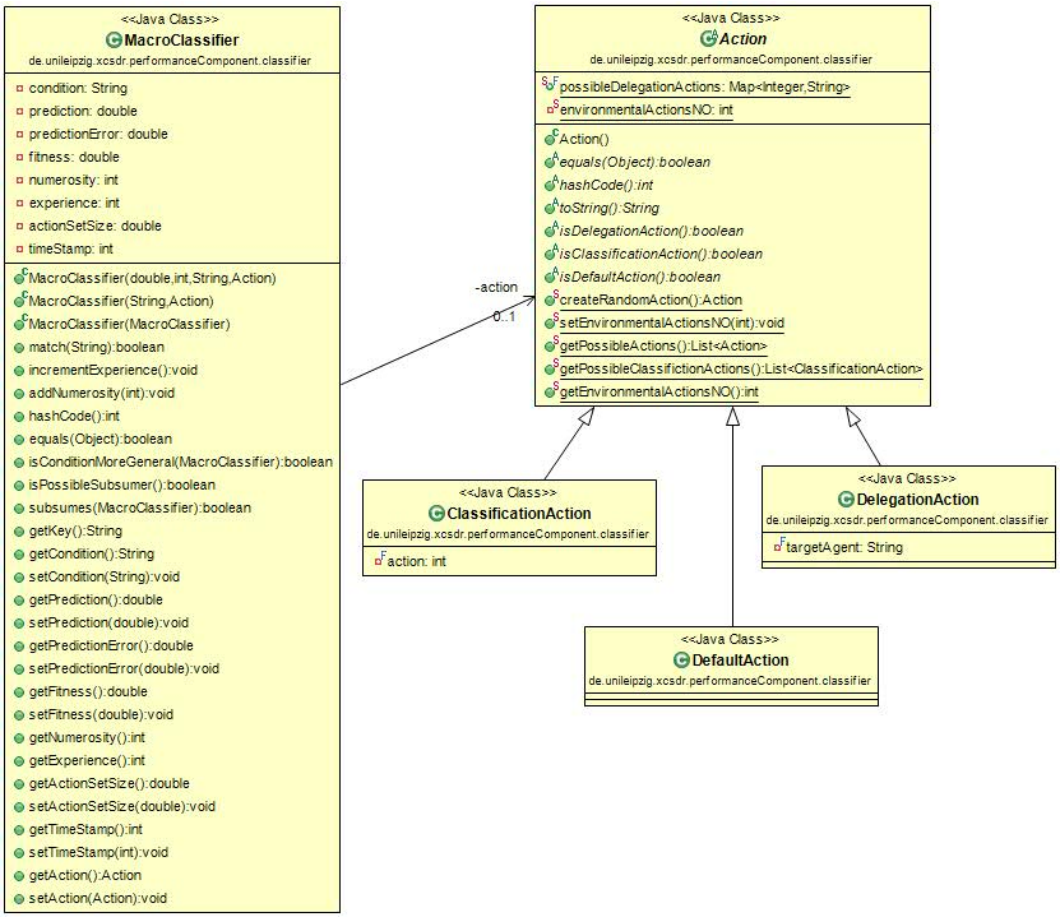


Figure 4.3: Class diagram of the package classifier. The classes that extend Action only implement the abstract methods defined by the parent class. Private methods are not displayed.

Action: Abstract class modeling the actions a classifier contains. It is the parent class of *ClassificationAction*, *DelegationAction* and *DefaultAction*.

ClassificationAction: A subclass of *Action*. It specifies an action to be executed on the environment.

DelegationAction: A subclass of *Action*. It specifies the ID of a targetAgent.

DefaultAction: A subclass of *Action*. It represents the 'null action'. It is used only during covering if no action is missing.

Subpackage classifierSets The package classifierSets contains the implementations of all kinds of classifier sets such as the population and match set. The general class *AgentClassifierSet* provides functionality that all specific classifier sets have in common, such as accessing contained classifiers. An instance of *AgentClassifierSet* contains several instances of *ClassifierAgent,* that in turn contains a collection of macro-classifiers. See figure 4.4 for the according class diagram of this package.

AgentClassifierSet: Parent class of all specific classifier sets. It contains a limited amount of instances of *ClassifierAgent*. This class provides methods for adding and deleting classifiers to and from the contained instances of *ClassifierAgent* as well as auxiliary functionality.

ClassifierAgent: An instance of this class contains a limited amount of instances of *MacroClassifier*. Instances of *ClassifierAgent* are identified within their according *AgentClassifierSet* by an ID. The maximum number of contained macro-classifiers is specified in the config file.

AgentPopulation: A subclass of *AgentClassifierSet*. It represents the actual population of classifiers. Provides methods for insertion and deletion of classifiers.

AgentMatchSet: A subclass of *AgentClassifierSet*. This class implements the match set construction and covering mechanism.

AgentActionSet: A subclass of *AgentClassifierSet*. It represents the action set and provides functionality for action set formation and action set subsumption.

4.3.4 Package reinforcementComponent

ReinforcementComponent consists of classes providing the functionality for distributing payoff and updating classifier parameters.

ActionSetUpdater: This class provides the different action set update procedures. *ActionSetUpdater* determines the amount of payoff that each classifier receives and controls the parameter updates of all classifiers of an action set. Which update procedure is executed depends on the mode of execution.

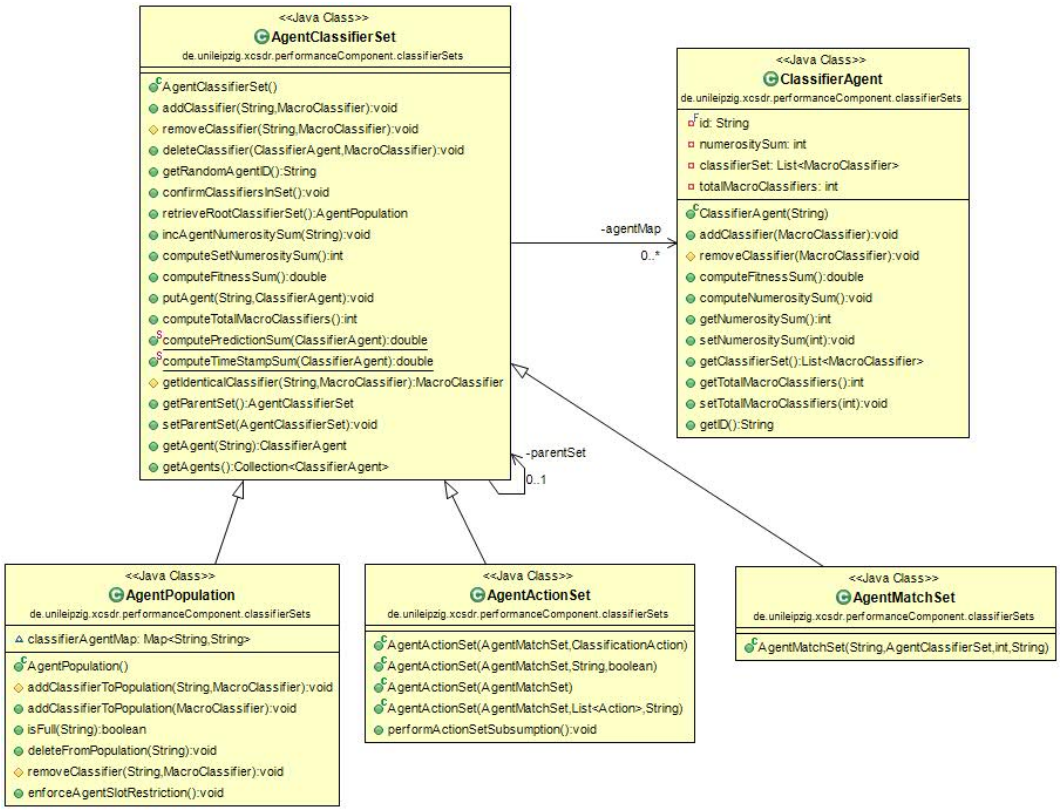


Figure 4.4: Class diagram of the package classifierSets. Private methods are not displayed.

ClassifierUpdater: This class computes and sets the actual update values of all parameters of a single classifier. It provides the according Widrow-Hoff formulas and implements the MAM technique.

4.3.5 Package discoveryComponent

Contains the genetic algorithm of the XCS-DR implementation. The covering mechanism is not part of this package but rather placed directly inside the class *AgentMatchSet* of the package classifierSets. This is because the covering procedure is a very simple one and at the time of development it seemed reasonable to implement it where it is executed.

AgentGeneticAlgorithm: This class provides the method *runGA()* that executes the entire genetic algorithm, from selecting two parent classifiers for replication to inserting the newly created offspring classifiers into the population.

4.3.6 Package utils

The utils package mainly implements auxiliary functionality. It provides classes that are unrelated to the specification of XCS-DR but necessary for correct program execution. It is responsible for reading the config parameters and recording the system performance during exploit. The classes in this package are very loosely related. An introduction of every single class of this package is omitted here since they do not provide functionality specific to XCS-DR.

4.4 Running the Program

The project directory contains an executable Java Archive file, xcs-dr.jar. To run the program, navigate to the file and execute *'java -jar xcs-dr.jar'* in the command prompt. This executes XCS-DR by applying the parameters specified in a config.properties file. XCS-DR either uses the config file that is stored in the same directory as the jar file or if there is no such file, it applies a default one that is included within the jar file. In contrast to XCSJava 1.0, the program does not accept any command line arguments. All important program settings

are specified within the config file. Figure 4.5 shows the default config file that is included in the file xcs-dr.jar.

Some configuration parameters are specific to certain types of problems. For instance, is the parameter *payoff-type* specific to the multiplexer problem. The values of such specific parameters are relevant only if the *problem-type* parameter is set to a certain value and ignored otherwise. I.e. if the user enters IPP or MAZE as *problemtype*, the value of *payofftype* will be ignored during execution. The following listing provides a short description of each configuration parameter.

dont-care-prob: Specifies the probability of inserting dont-care symbols into a classifier's condition during covering. Every position of the condition is turned into a dont-care symbol with that probability.

mutation-prob: Specifies the probability of mutating a classifier's condition and action during GA execution. Every position of the condition and the action are mutated with that probability.

random-entry: Specifies whether the entry-agent is random or the same for every problem instance.

fitness-threshold: Classifiers with a fitness below or equal to that threshold are being ignored during prediction calculation.

agents: Specifies the number of agents in the population.

slot-no: Specifies the number of classifier slots per agent. This parameter constitutes the limit for the sum of the numerosities of all macro-classifiers contained in one agent.

problem-type: Specifies the particular problem to solve. Can be set to *MP* for the multiplexer problem, *IPP* for the incremental parity problem and *MAZE* for various predefined maze problems.

output-dir: Specifies the directory where all output files are saved to. The output is written after all experiments finished.

trials: Specifies the number of exploit cycles of one experiment. Before each exploit, a classification explore and a delegation explore cycle

is executed. Hence, the system executes three times as many problem instances as defined by this parameter.

experiments: Defines the number of experiments executed consecutively. The length of an experiment is defined by the *trials* parameter. After execution of a given number of exploit cycles (specified by the *trials* parameter), one experiment is finished.

prob-length: Specific to the IPP and MP problem types. It defines the number of bits that each problem instance consists of. While for the IPP arbitrary problem lengths are possible, the MP has to be of length $k + 2^k$. The system still accepts arbitrary problem lengths for the MP. In case *prob-length* is not of length $k+2^k$, the largest multiplexer that fits the specified length is created and the supernumerous bits are assigned random values by the environment for each problem instance.

payoff-type: Specific to the MP problem type. If it is *0* the systems receives a reward of 1000 from the environment for every correct classification. If the value is set to *1* the system receives reward according to the payoff map described previously in section 4.1.1.

maze: Specific to the MAZE problem type. Specifies the particular maze to apply. Possible values are Woods1, Woods2, Maze4, Maze5 and Maze6. The according maze definitions are included as text files in the resources folder of the project's sources.

encoding: Specific to the MAZE problem type. Possible values are 2 and 3. Specifies the number of bits that each position in a maze is encoded with. Woods2 is usually encoded with 3 bits and Maze4 typically with 2 bits. This parameter has simply been adopted from XCSJava 1.0. The documentation of XCSJava 1.0 does not provide much information about specific encodings.

```
#XCS configuration:
dont-care-prob=0.1
mutation-prob=0.04
random-entry=false
fitness-threshold=0.01


#Agent configuration:
agents=5
slot-no=800


#Environment configuration
#Possible problem types - MP, IPP, MAZE:
problem-type=MP
output-dir=C:\\XCS_data
trials=20000
experiments=1

#MP and IPP specific
prob-length=11

#MP specific
#(possible types - 0, 1):
payoff-type=1

#Maze specific
#Possible mazes: Woods1, Woods2, Maze4, Maze5, Maze6
maze=Woods2
#Possible encodings: 2, 3
encoding=3

```

Figure 4.5: The default config.properties file.

4.5 Editing and Compiling the Sources

XCS-DR has been implemented with the project management tool Apache Maven. Maven is a tool that provides support during all stages of the software development process, such as automating the build process, managing dependencies, reporting and documentation and more. Every Maven project is specified by a XML file, the pom.xml, which defines the project configuration. Maven enforces a package structure that contains the domain name of the company that is hosting the software project. The source code of XCS-DR has been created by a student of Universität Leipzig and the according domain name is uni-leipzig.de. Since Java does not allow packages to contain hyphens, all packages are prefixed with de.unileipzig.xcsdr, according to the Maven guidelines. This prefix constitutes the Maven groupId that uniquely identifies the project.

The sources of XCS-DR can be edited with any text editor or IDE that supports Java code. To access any Maven-specific functionality and create an executable Java Archive file (jar), Apache Maven has to be installed on the host computer. Some IDEs, such as Eclipse, provide build-in support for Apache Maven. To build the project and create an executable jar file from the sources, navigate to the project directory within the command prompt and execute *'mvn clean compile assembly:single'*. This builds the project and saves an executable jar in the 'target' folder of the project.

4.6 Output

XCS-DR provides two kinds of ouput. On the one hand in the console where the program is running and on the other hand writing output files in the specified output directory.

In the console, XCS-DR writes:

- The number of the current experiment
- The number of so far examined problems in exploit
- The average accuracy of the last 50 exploit cycles (single-step problems) resp. the average distance to food of the last 50 exploit cycles (maze problems)

- The total number of macro-classifiers in the population

Additionally, XCS-DR produces several output files that are created at the end of program execution, after all classifications finished. All files are saved to the output directory specified in the config file. The file accuracy.txt keeps track of the system's performance by either containing the average accuracy (single-step problems) or average distance to food (maze problems). The file pred_error.txt records the average prediction error, graph.txt keeps track of the delegations in the system and how many problem instances each agent classifies and number_of_classifications.txt and number_of_delegations.txt record the average totals of classifications resp. delegations in the population. The next chapter provides in detail explanations about how these quantities are measured.

The output directory can also contain a file population.txt that contains a snapshot of the classifier population. When the method logPopulation of the class PopulationLogger is called, the program writes every macro-classifier of the current population to that file. This class has mainly been in use during debugging and troubleshooting. The final program does not write any populations but by editing the source code it could easily be added.

Chapter 5

Performance Analysis

This chapter presents an analysis of XCS-DR's performance. The main points of interest are how accurately it classifies problem instances compared to the original and how different numbers of agents affect the performance. During every conducted experiment, the system has been provided with a high enough slot number such that the final performance of XCS-DR, after convergence of the classifier population, has not been affected negatively. This work mainly focused on the development of an accurately working agent-based XCS and this chapter investigates to what extent this goal has been reached. An extended investigation of different slot numbers and their effects on the performance could be part of future investigations. The term performance is used from now on interchangeably for *accuracy* if the system acts in a single-step environment respectively for *distance to food* if the system acts in maze environments. Experiments have been conducted for the 6-MP, 11-MP, 8-IPP, Woods2 and Maze4 problems. Although Maze6 is the most complex environment implemented by XCS-DR, Maze4 has been chosen as the most complex problem to pose to the system. This was due to the computational effort necessary to solve complex multi-step problems while maintaining several agents. Since most experiments have been repeated hundreds of times with different configurations, choosing an even more complex environment than Maze4 would have taken too much time of computation.

At first in this chapter are introduced all measured variables. Thereafter, it is investigated how the single-agent XCS-DR performs compared to XCSJava 1.0. The underlying principles of XCS have not been changed in XCS-DR and therefore a single-agent XCS-DR should be exhibiting the same performance as

XCSJava 1.0. The third section compares the different kinds of explore delegation procedures that have been introduced in the previous chapter and determines which one is working best. Thereafter, it is analyzed the performance of several multi-agent XCS-DR configurations in the 11-MP environment. The subsequent sections present a similar analysis of XCS-DR's performance in the 8-IPP, Woods2 and Maze4 environment. During the experiments conducted for the previously mentioned sections, the entry-agent of XCS-DR has been the same each cycle. Section 5.8 investigates how XCS-DR behaves when the entry-agent is determined randomly each time. The last section of this chapter provides an analysis of the emerging classification and delegation patterns of the agents. It is broken down how the classification and delegation of the input state is distributed between the agents.

As long as not mentioned otherwise, are all parameter settings in the experiments the ones applied by XCSJava 1.0. Note that during all multiplexer experiments, the in section 4.1.1 introduced payoff map has been applied by setting the parameter *payoff-type* to 1.

5.1 Measured Variables

XCS-DR measures several quantities during the exploit phase that describe the behavior of the system and how it performs. The most important measurement is *accuracy* in single-step environments respectively *distance to food* in maze environments as both are ultimately recording the system's performance.

Average Accuracy Measured only for single-step problems. XCSJava 1.0 measures how many of the last 50 problem instances have been classified correctly during exploit and calculates the average. Therefore, the system provides an accuracy value every 50 exploit steps. This procedure has been adopted by XCS-DR. The resulting accuracy averages are averaged again over several experiments. Since accuracy values are provided only every 50 steps, the resulting accuracy curve looks choppy. By conducting many experiments, deviations have been smoothed out. This data is provided by the output file accuracy.txt.

Average Distance to Food This is the equivalence of the accuracy in the implemented multi-step problems. Instead of measuring whether a problem

instance has been classified correctly, the system records the number of steps necessary to reach food. The overall procedure is the same as for the accuracy, averaging every 50 steps and over several experiments. The data is contained in the ouput file accuracy.txt.

Proportionate Classifications Records for each agent how many problem instances have been classified during exploit. A problem instance is classified by an agent, if this agent determines the action that is executed on the environment. This measure is calculated relative to the total number of classifications and averaged over several experiments. Proportionate classifications are recorded in the output file graph.txt.

Proportionate Delegations: Records for each pair of agents how many problem instances have been delegated between them during exploit. This measure is calculated relative to the total number of delegations and averaged over several experiments. The directions of delegations are considered. There is a separate value for the delegation $Agent_i \rightarrow Agent_k$ and another one for $Agent_k \rightarrow Agent_i$. This quantity and the previous one are useful for analyzing the emerging classification and delegation patterns. Proportionate delegations are also recorded in the output file graph.txt.

Number of Classifications Records during each exploit cycle the total number of classification classifiers in the system. It is calculated by adding up the numerosities of all classifications of all agents and averaged over several experiments. This data is contained in the output file number_of_classifications.txt.

Number of Delegations Records during each exploit cycle the total number of delegation classifiers in the system. It is calculated by adding up the numerosities of all delegations of all agents and averaged over several experiments. This quantity and the previous one determine how many slots of the system are occupied by each kind of classifier. This data is contained in the output file number_of_delegations.txt.

Average Prediction Error The average prediction error is recorded just as the average accuracy. It is averaged over 50 steps and multiple experiments.

The average prediction error is written to the file pred_error.txt. It is not considered during the performance analysis. Mainly, since the actual differences in classification performance are of interest. To address that issue, the prediction error does not provide any additional information.

5.2 Comparison of XCSJava 1.0 with XCS-DR

XCS-DR is able to function by maintaining only a single agent. It was a goal to design XCS-DR in a way that it performs equally to XCS, if it applies only one agent. This section examines how accurately a one-agent XCS-DR performs. Although maintaining only one agent makes delegations obsolete, the delegation explore procedure is still executed as usual. The delegation explore mode that is applied by the single-agent XCS-DR is 'Global Best, Random Target', simply because this was the first one that has been tested. Which delegation explore strategy is applied in this scenario does not make a difference since delegations are of no value to the system and the reinforcement component never rewards delegations pointing to their home agent.

In the best case, the performance of a single-agent XCS-DR would be identical to XCSJava 1.0. In the conducted experiments both systems apply the same parameter settings, the ones that are applied by XCSJava 1.0 and both have the same amount of slots. Figure 5.1 shows a performance comparison between XCSJava 1.0 and the single-agent XCS-DR in the 11-MP, Woods2 and Maze4 environment. All experiments have been conducted 100 times and the resulting curves present the averages. The IPP is not part of this performance comparison since it was not implemented by XCSJava 1.0.

As can be seen in figure 5.1a, both systems reach maximum accuracy in the 11-MP environment but XCS-DR needs slightly more steps to do so. This is most likely due to delegations evolving in parallel that are blocking slots that could otherwise be occupied by classifications. Figure 5.1b depicts the evolution of the total numbers of classifications and delegations in this scenario. The number of delegations is rising quickly in the beginning as long as there are still free slots in the system and no classifiers get deleted. The peak of the delegation curve denotes the point where there are no free slots in the system anymore. Thereafter, more delegations than classifications are being deleted, due to their low fitness, which leads to a sharp decline in the number of del-

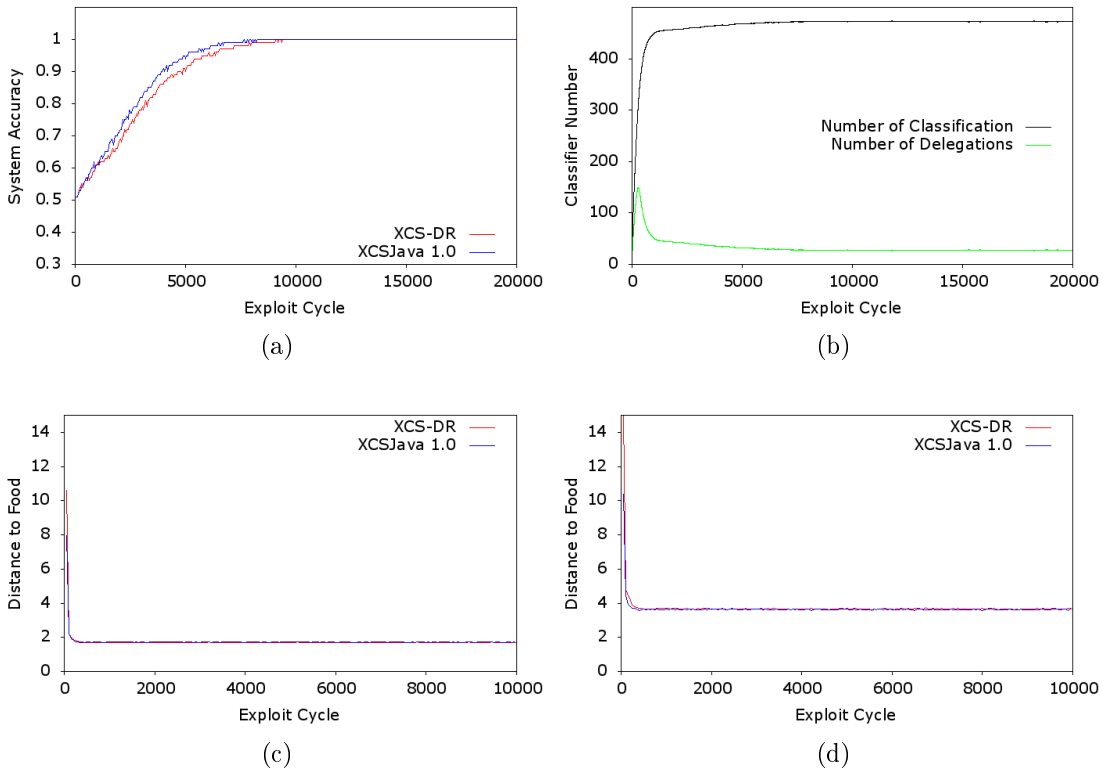


Figure 5.1: Performance comparison between the single-agent XCS-DR and XCSJava 1.0, averaged over 100 experiments. 11-MP, 500 slots (a); Woods2, 1000 slots (c); Maze4, 1000 slots (d). Evolution of the classifier population of the single-agent XCS-DR in the 11-MP, 500 slots (b).

egations. Nevertheless, are those delegations blocking slots which also forces some classifications to be deleted earlier than in the original. This effect delays the evolution of classifications and therefore delays the evolution of the system accuracy.

Figure 5.1c compares the performances of both systems in the Woods2 environment. As can be seen there is almost no difference between both curves except in the very beginning. The previously discussed negative impact of additional delegations is not taking place here. The analysis of the collected data about the total number of classifications and delegations and experiments with lower slot numbers have shown that the slot number is high enough to prevent a negative impact of delegations during early exploit cycles.

Figure 5.1d is pretty similar to Figure 5.1c and provides a comparison of the performances of XCSJava 1.0 and the single-agent XCS-DR in the Maze4 environment. Again, there is only a very small difference between the average distances to food.

5.3 Comparison of the Delegation Explore Modes

This section compares the various introduced delegation explore modes. It is the goal to determine the delegation explore mode that suits best for any environment. To determine the best explore mode, all of them have been probed in several environments (6-MP, 5-IPP and Woods2). The chosen environments are of moderate complexity but suffice to point out two deficient strategies. Only the two more reliable approaches are tested in the more complex Maze4 environment. To determine the best procedure, only the average accuracies respectively average distances to food have been compared. As long as the average performance of a certain procedure is better after the classifier population converged, that delegation explore scheme is considered superior to approaches performing worse. All initial experiments have been conducted with three agents. The fitness threshold of the prediction array was set to 0.01. The experiments conducted in this section only serve to determine the best delegation explore procedure.

Figure 5.2 shows how all four delegation explore approaches performed in the 6-MP, 5-IPP and Woods2 environment. Figures 5.2a and 5.2b illustrate their performance in the two single-step environments. As one can see, for

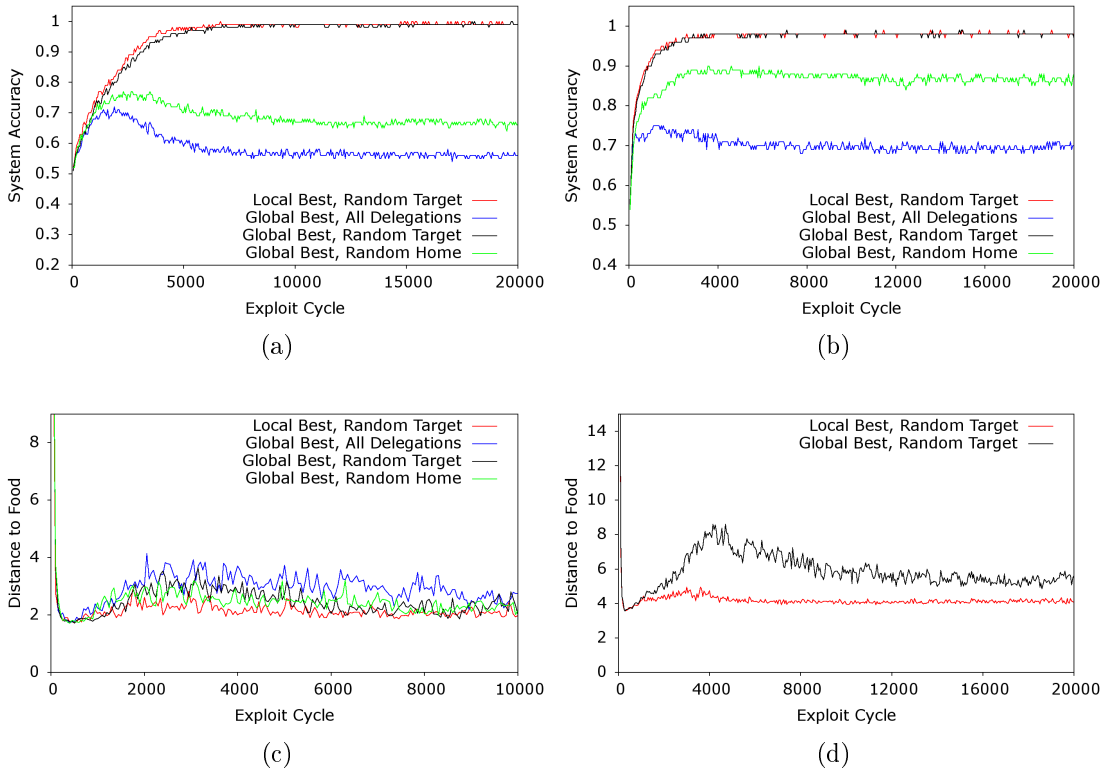
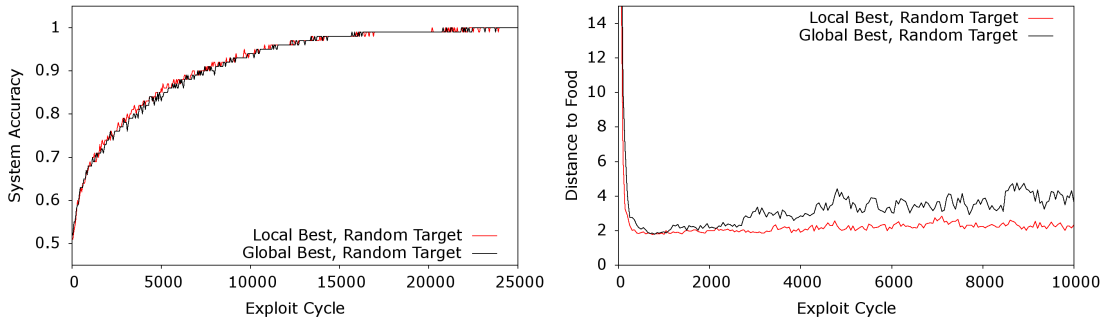


Figure 5.2: Evolution of the system accuracy/distance to food of the different delegation explore modes, in a 3-agent XCS-DR, depending on the exploit cycle. 6-MP, 500 slots, 100 experiments (a); 5-IPP, 800 slots, 100 experiments (b); Woods2, 800 slots, 50 experiments (c); Maze4, 1800 slots, 100 experiments (d).

the 6-MP and 5-IPP, two strategies reach an accuracy of almost 1.0 and two others significantly lack performance. In the 6-MP environment the 'Global Best, All Delegations' strategy reaches an accuracy that is only slightly above 0.5. This is almost as bad as if one guessed the correct classification for a given problem instance. In the 5-IPP it performs a bit better. Since 'Global Best, All Delegations' is yielding such insufficient results in these two single-step environments, in can not be considered a valid option to be applied by XCS-DR in general. This is the same for the 'Global Best, Random Home' approach. Although it is performing better than the previously discussed strategy, it is not getting close to the accuracies of the two top-performers. Between 'Local Best, Random Target' and 'Global Best, Random Target', the first one is yielding better accuracy by only a tiny margin. One can see that in figure 5.2a as well as 5.2b it is peaking more often to 1.0 accuracy. These are minor differences so that both delegation explore modes can be considered equally accurate in these environment.

Figures 5.2c and 5.2d investigate the performance of the different delegation explore modes in two multi-step environments. In both cases the performance is best if the average distance to food is minimal. In the Woods2 environment the deviation and peaks are much greater compared to the other environments. This is because only half as many experiments have been conducted to determine the averages due to the long time of computation. 'Local Best, Random Target' is performing best with the smallest peaks and least deviation. 'Global Best, Random Target' is performing notably worse than 'Local Best, Random Target' and approximately equal to 'Global Best, Random Home'. 'Global Best, All Delegs' is the worst strategy again.

Since 'Global Best, Random Home' and 'Global Best, All Delegs' have not stood out positively in either one of the investigated environments, they are not considered any further. Due to 'Local Best, Random Target' and 'Global Best, Random Target' being serious competitors, there has been conducted an additional experiment in the more complex Maze4 environment. As can be see in figure 5.2d, 'Local Best, Random Target' is performing better by a very wide margin.



(a) (b)

Figure 5.3: Evolution of the system accuracy/distance to food of different delegation explore modes, depending on the exploit cycle. 8-IPP, 15 agents, 70000 slots, 100 experiments (a); Woods2, 10 agents, 5000 slots, 50 experiments (b).

5.3.1 More Complex Problems and Agent Structures

The previously investigated performances are all based on XCS-DR instances with 3 agents. However, the different delegation explore strategies might perform differently when having to maintain a more complex agent structure. Also, the complexity of the environment might influence performances. Therefore, figure 5.3 shows the performances of the 'Local Best, Random Target' and 'Global Best, Random Target' approaches solving the 8-IPP maintaining 15 agents (figure 5.3a) and Woods2 maintaining 10 agents (figure 5.3b). The other two approaches are not considered any further due to their inefficiency. As can be seen 'Local Best, Random Target' is performing equal to 'Global Best, Random Target' in the IPP environment and vastly superior in Woods2. Hence, the collected data has shown that regardless of the applied number of agents and structure of the environment, 'Local Best, Random Target' is the best delegation explore mode for all implemented environments. As a result, all future experiments are conducted applying that strategy.

5.4 The 11-Multiplexer Problem

Figure 5.4 presents an overview of the accuracies of a 5-agent, 10-agent and 15-agent XCS-DR compared to XCSJava 1.0. The parameter settings different from XCSJava have been: probability of # during covering = 0.1, fitness threshold = 0.01 and entry-agent = $Agent_0$. As can be seen, none of the agent-based

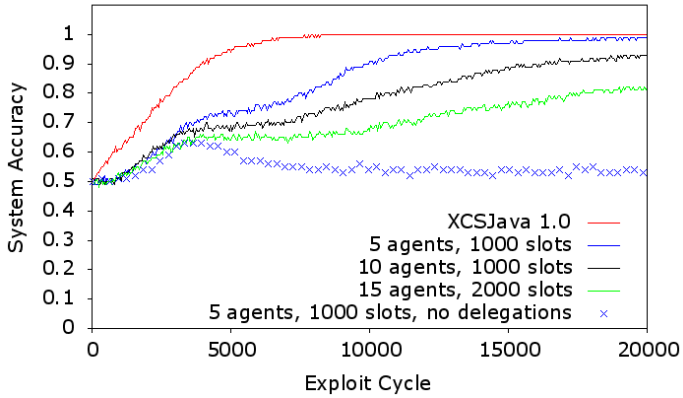


Figure 5.4: Evolution of the system accuracy of XCS-DR depending on the exploit cycle in the 11-MP environment. Averaged over 100 experiments.

configurations of XCS-DR is converging as quickly as the original. Also, none of the agent-based configurations reaches an accuracy of true 100%. The 5-agent XCS-DR gets close but remains below the XCSJava curve. Additionally, it is obvious that with an increasing number of agents the performance declines noticeably. While the 5-agent system reaches an accuracy of almost 1.0, the 15-agent XCS-DR converges at around 0.8. Note that there is some kind of two phase convergence taking place in the XCS-DR configurations. First, the accuracy rises sharply until a certain plateau is reached for a while, just to rise again slower thereafter. The reason for that might be found in the different time spans it takes for classifications and delegations to evolve. It is possible that the first rise in accuracy is due to the quick evolution of classifications and the second one due to the slower evolution of delegations.

The decline in accuracy with rising numbers of agents in XCS-DR shows that the evolution of delegations is not yet working perfectly. In the evolving populations it is striking that there are evolving many delegations of the kind ########## : $Agent_i$ with a *prediction* close to 0. These overgenerals reach high fitnesses and huge numerosities compared to useful delegations. Their numerosites are about ten times higher compared to the numerosities of valuable delegations. Even if an agent is holding various useful classifications, such an overgeneral delegation that predicts 0 payoff is emerging. Changing the probability of dont-care symbols during covering did not have a positive effect. The fact that these overgenerals with high fitnesses and numerosities are appearing, indicates that the reinforcement component has to be improved to

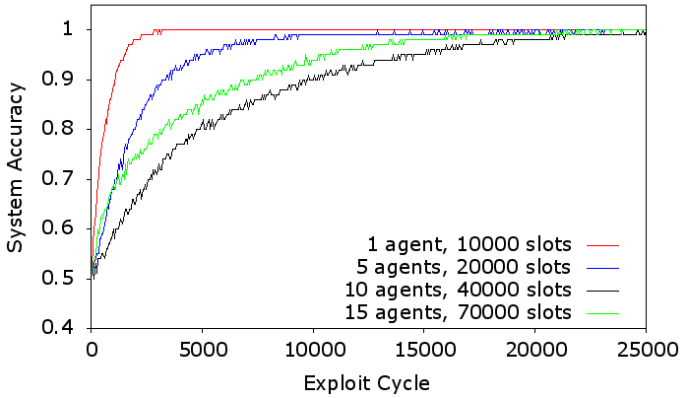


Figure 5.5: Evolution of the system accuracy of XCS-DR depending on the exploit cycle in the 8-IPP environment. Averaged over 100 experiments.

prevent their emergence. Unfortunately, this could not be achieved within the scope of this work. Nevertheless, figure 5.4 shows that delegations are of value to the overall performance. The blue, dashed curve presents the performance of a 5-agent XCS-DR with disabled delegations during exploit. In such a manipulated XCS-DR, all explore steps are taking place as usual and the population is evolving normally but during exploit, all problem instance have to be classified by the entry-agent. As can be seen, this leads to an accuracy only slightly better than guessing, proving that the delegations are still contributing to the correct classification of problem instances.

5.5 The 8-Incremental Parity Problem

Figure 5.5 shows the performance of XCS-DR in the 8-IPP environment. The parameter settings have been: probability of # during covering = 0.0, fitness threshold = 0.01, entry-agent = $Agent_0$ and mutation probability = 0.01. The reason for the low # probability and mutation probability is that the IPP is a problem that has no generalization potential. Setting those probabilities higher would have led to overgenerals in the population, resulting in a lot of misclassifications. This is also the reason for the high slot numbers as many more classifiers are necessary to correctly solve the 8-IPP than the 11-MP. Apparently, XCS-DR is handling the 8-IPP better than the 11-MP. All configurations converge towards an accuracy higher than 0.98. There is no curve provided displaying the performance of XCSJava 1.0 since the IPP environment has not been

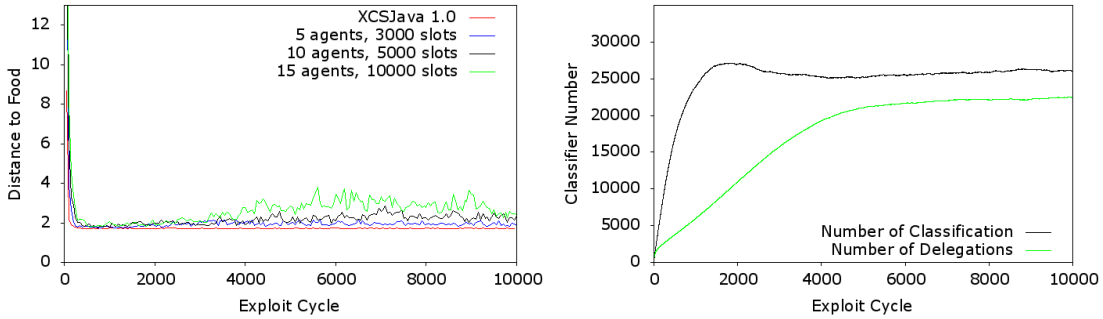
implemented by XCSJava 1.0. XCS-DR is performing much better in the IPP environment than in the MP environment. This is due to the complex payoff map applied to the MP environment. In the IPP, payoff is much simpler structured. The system receives a reward of 1000 for correct classifications and 0 for incorrect ones. When applying this simpler payoff structure to the MP it is also performing much better. Additionally, it is obvious that there are no different phases in the evolution of the system accuracy in the IPP environment, as it occurred in the MP environment.

The striking observation resulting from figure 5.5 is that the 15-agent XCS-DR is performing better than the 10-agent XCS-DR. One might assume that there have simply not been provided enough slots for the 10-agent system to work properly. Surprisingly, experiments with a 10-agent XCS-DR maintaining as many slots as the 15-agent system have not improved the accuracy of that configuration. It is not possible to conclude, whether their equal performance is a side effect of the reinforcement component having to be improved or whether the agent structure itself is affecting performance regardless of the slot number. Further experiments would have to be conducted to clarify that. A similar, but weaker, effect is taking place in the Maze4 environment as well.

5.6 Woods2

The performance of XCS-DR in the Woods2 environment is displayed by figure 5.6. The applied parameter settings have been: probability of # during covering = 0.1, fitness threshold = 0.01, entry-agent = $Agent_0$. The performance is averaged over only 50 experiments, due to the long computation time of multi-step problems. As can be seen, the performances of the 5- and 10-agent configuration are pretty close to XCSJava 1.0. The 15-agent XCS-DR is displaying much higher deviations and requires on average about one more step to reach food. This seems still acceptable regarding the fact that the system has to coordinate 15 agents.

The cycles 500 to 2000 are eye-catching as the performances during this period are almost equal to the original for all XCS-DR configurations. It is not totally clear why the average distance to food rises thereafter. The classification explore procedures of XCS-DR and XCSJava 1.0 are the same and the evolution of maximally successful classifications finishes after about 400 steps. This can be



(a) (b)

Figure 5.6: Evolution of the distance to food of XCS-DR depending on the exploit cycle in the Woods2 environment, averaged over 50 experiments (a). Evolution of the classifier population of the 10-agent XCS-DR in Woods2, 5000 slots, 50 experiments (b).

concluded by examining the curve of XCSJava 1.0. During subsequent exploit steps, XCS-DR performs almost as well as XCSJava 1.0 but the average distance to food increases later on.

Is it possible that the corresponding entry-agent is simply holding the sufficient amount of classifications during that period to perfectly solve all Woods2 instances? This assumption does not hold true. When delegations are disabled during exploit, XCS-DR performs much worse at all times. The according curve is not shown in the figure to preserve readability. However, this suggests upon reversion, that in the standard XCS-DR configurations not only the classifications are best during that period of time, but also the delegations are working fine. Otherwise, XCS-DR would not perform equally to XCSJava 1.0 in that period. Figure 5.6b shows the evolution of the total numbers of classifications and delegations in the 10-agent XCS-DR. As can be seen, there is a correlation between the increasing number of delegations in the system and the decline in performance of the 10-agent XCS-DR. However, the total amount of classifications is relatively stable after peaking early. This suggests that the rising number of delegations is somehow interfering with the classifications of the system while not significantly affecting their total number.

Unfortunately, the collected kind of data is not sufficient to draw any final conclusions. It is not clear whether the decline in performance after early exploits is resulting from a flawed delegation explore procedure or the ratio between total classifications and total delegations or some other cause. Further investigations

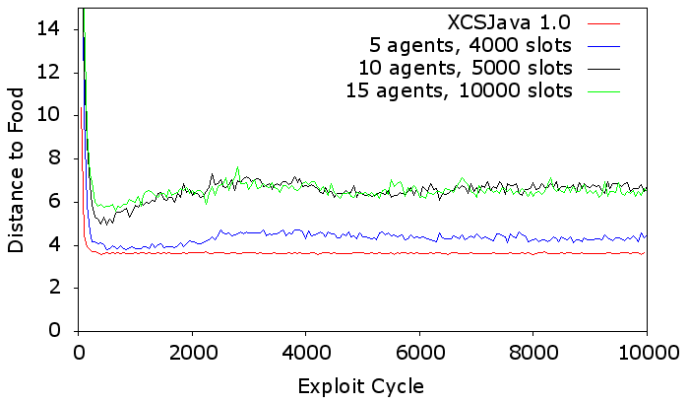


Figure 5.7: Evolution of the distance to food of XCS-DR depending on the exploit cycle in the Maze4 environment. Averaged over 100 experiments.

would be necessary to clarify how delegations and classifications evolve and interact in that environment and why the average distance rises after being astonishingly low during early exploit steps.

5.7 Maze4

Maze4 is the most complex environment in which XCS-DR has been tested. The system behaves similar in it compared to Woods2. Figure 5.7 displays the average distances to food of several multi-agent XCS-DR configurations. The applied parameter settings have been the same as in the previous section with the exception that the performance was averaged over 100 experiments. Although this was computationally intensive and cost a lot of time, averaging over 100 experiments provided smoother curves and less deviation. As can be seen in the figure, the 5-agent configuration is not much worse than XCSJava 1.0. Surprisingly, the 10- and 15-agent configurations are performing almost equally well with the 15-agent configuration regularly beating the 10-agent system after about 7000 exploits. A similar effect could be witnessed much clearer in the 8-IPP environment where the 15-agent system obviously outperformed the 10-agent system. It is obscure, in this case as well, whether a flawed delegation explore procedure or the agent structure itself is responsible for this effect. Also, the in the previous section scrutinized effect of low distances during early exploit cycles is taking place. This might be typical for maze environments although it is not happening as clearly in the more complex Maze4 environment as it

is in Woods2. Generally, the 15-agent system is performing about 50% worse than the original which is a similar result compared to Woods2. The 10-agent configuration performs much worse in Maze4 relative to Woods2. The average distances achieved seem still acceptable regarding the fact that the delegation explore procedure is not yet reinforcing optimal delegations. The food is discovered with delay by XCS-DR compared to XCSJava 1.0, but it is still performing much better than a randomly moving animat would.

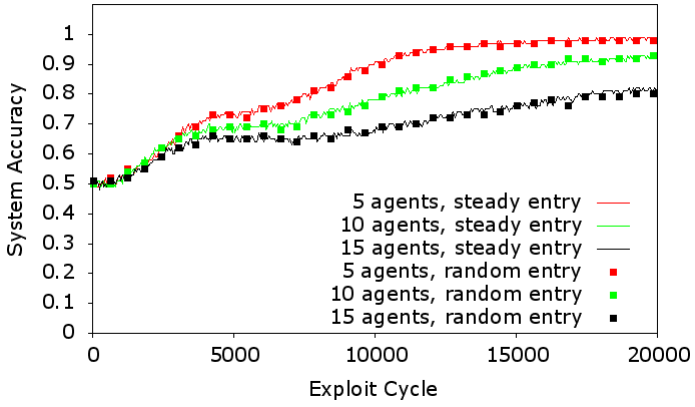
5.8 Random Entry-Agent

Figures 5.8 and 5.9 show the performances of several XCS-DR configurations when the entry agent is chosen randomly each cycle. The configuration parameters during each experiment have been the same as in the according fixed entry-agent experiment.

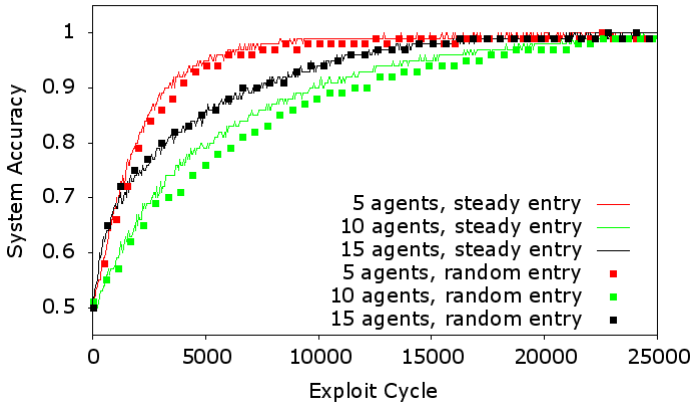
As can be seen, in certain situations such a configuration performs slightly worse compared to its fixed entry-agent counterpart (such as the 10-agent 8-IPP configuration) and in others it performs better (such as 10-agent Woods2). In most cases the performances of the random-entry configurations almost perfectly match the according performances in a fixed-entry system except for slight statistical deviations. The system displays the desired behavior of all agents being of equal importance and capable of handling the input state. The emerging structures are not asymmetric ones whose performance is dependent on a distinguished superior entry-agent. To create a system of equal, interacting agents was one of the design goals of XCS-DR and the performance curves presented in this section show that this goal has been achieved.

5.9 Classification and Delegation Patterns

This section provides an analysis of the emerging delegation structures in XCS-DR as the classifier population evolves. It is scrutinized how many problem instances each agent classifies and what kinds of delegation patterns evolve. The delegation and classification patterns are visualized as graphs. Each node in such a graph represents an agent of XCS-DR and the size of each node corresponds to the relative number of problem instances the according agent has classified. Each directed edge between two agents indicates that delegations

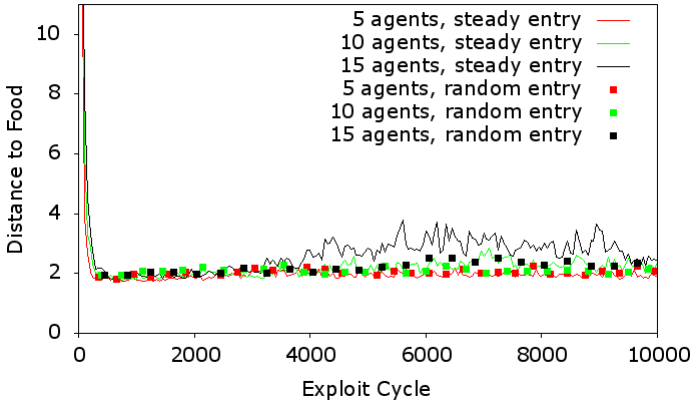


(a)

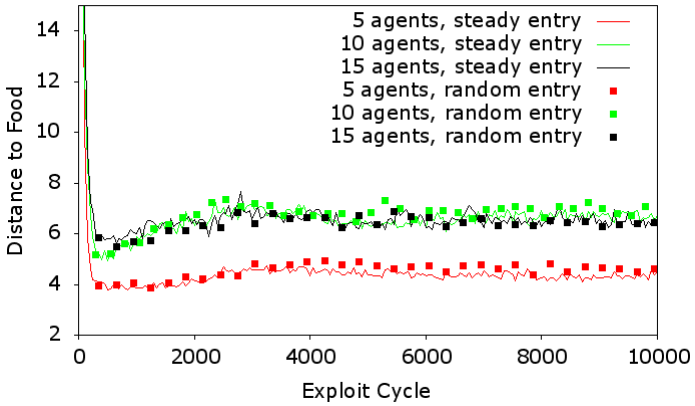


(b)

Figure 5.8: Evolution of the accuracy of XCS-DR with random and steady entry-agent. Slot numbers and numbers of experiments are equal to the corresponding steady entry-agent experiments. In the 11-MP environment (a); in the 8-IPP environment (b).



(a)



(b)

Figure 5.9: Evolution of the distance to food of XCS-DR with random and steady entry-agent. Slot numbers and numbers of experiments are equal to the corresponding steady entry-agent experiments. In the Woods2 environment (a); In the Maze4 environment (b).

have been taken place. The width of an edge corresponds to the relative number of problem instances that have been delegated along this edge. All the graphs presented in this section are derived from the previously presented experiments. No additional experiments have been conducted. The particular configuration that led to each graph, can be found in the according previous section in this chapter. E.g., the graph representing the 11-MP, solved by a 5-agent XCS-DR with fixed entry-agent, was obtained from the experiment introduced in section 5.4, The 11-Multiplexer Problem. Next are discussed evolving delegation and classification patterns in fixed entry-agent configurations. Thereafter, random entry-agent configurations will be analyzed.

5.9.1 Fixed Entry-Agent

Figure 5.10 displays the resulting graphs of one particular configuration of each previously analyzed problem type. It is obvious that the entry-agent ($Agent_0$) is much bigger in each graph than all the other agents. Also, the remaining non-entry-agents are of almost equal size. This means that the entry-agent is classifying a significantly higher portion of the problem instances compared to the other agents and that all remaining agents are classifying equal numbers of problem instances. The edges that are outgoing from the entry-agent are very strong and all of them are of similar strength, whereas edges between other agents are almost non-existent. This means that the vast majority of delegations is taking place from the entry-agent to the other agents. The entry-agent distributes the problem instances, that it is not classifying, evenly to other agents but the receiving agents rarely delegate the input state again. All graphs with fixed entry-agent follow these two patterns. However, delegations are more even in the maze problems, where non-entry-agents also delegate to each other. Nevertheless, the general patterns are still obvious. Only some exemplary graphs are shown in the figure, since the graphs of other configurations look very similar.

These observations go hand in hand with the previously presented data about the overall system performance. Since the correct classifiers for each situation are distributed evenly among all agents, the entry-agent classifying more than others must introduce a certain error to the system. As could be seen in the previous sections, this is exactly the case as the XCS-DR configurations perform worse than the original. Especially, if the total number of agents rises. The reason

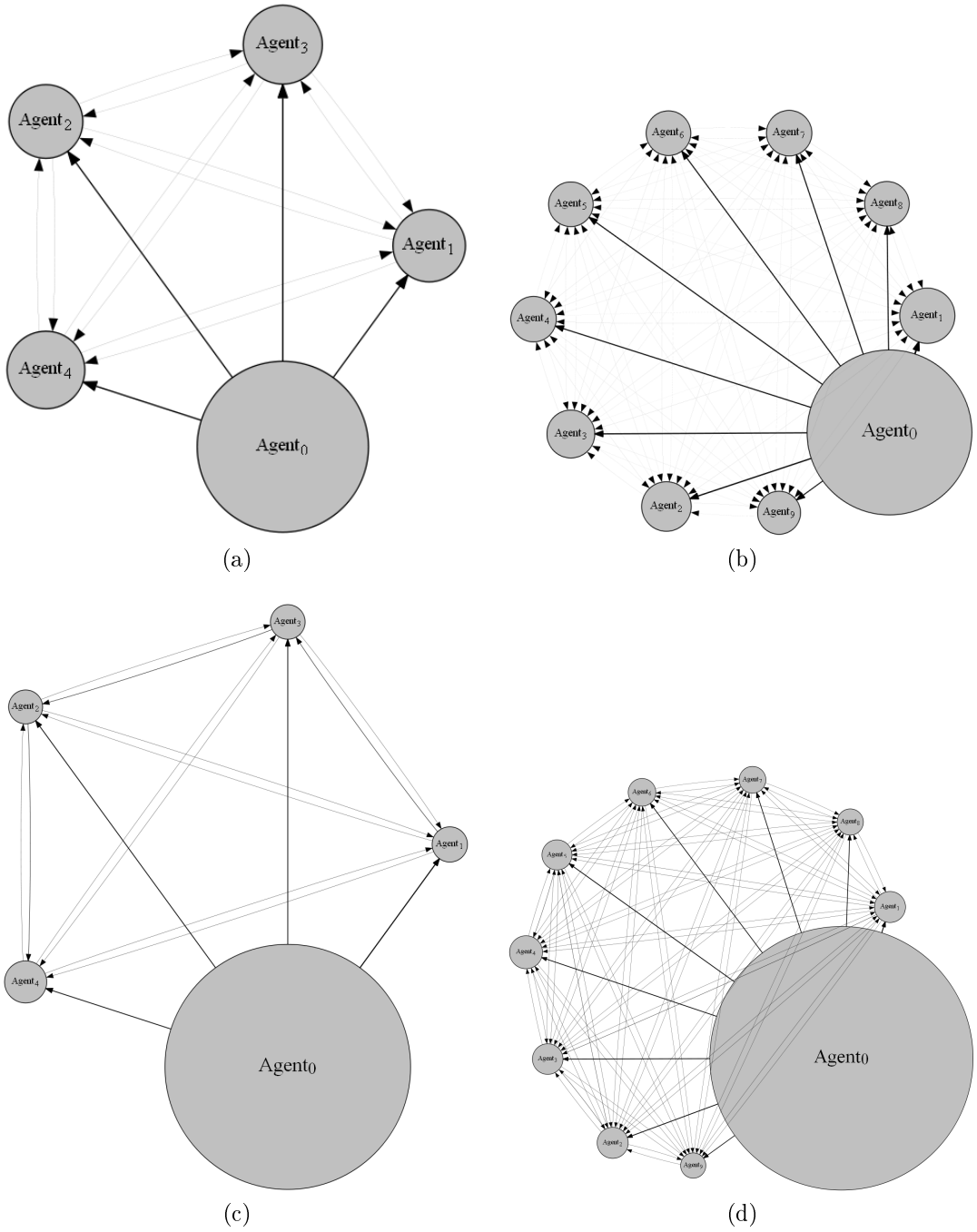


Figure 5.10: Classification and delegation patterns of XCS-DR with steady entry-agent. 11-MP, 5 agents (a); 8-IPP, 10 agents (b); Woods2, 5 agents (c); Maze4, 10 agents (d). All configuration parameters have been the same as in the corresponding performance experiments.

for the entry-agent classifying more problem instances, as concluded previously, is due to the evolution of delegations not working perfectly. Further more, in a perfectly efficient and accurate system there would be almost no delegations between non-entry-agents taking place. If so, only during early steps when the population of classifiers is still evolving. Since delegations are spread across all agents by the discovery component, every agent accesses the same information about potential payoffs of other agents. Hence, if two non-entry-agents delegate to each other, the entry-agent should have delegated to the final destination in the first place.

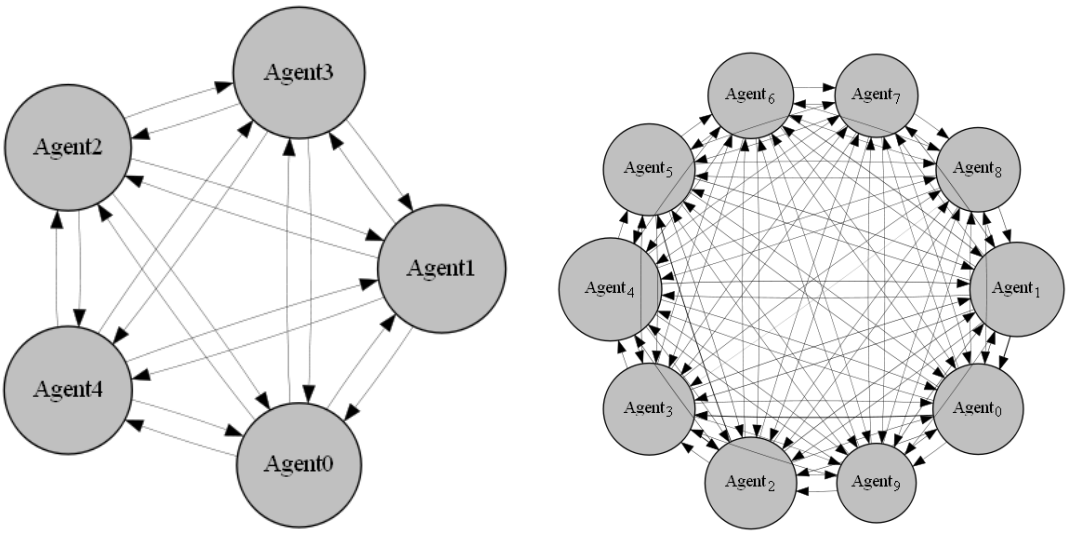
It is peculiar that in the maze environments the entry-agents classify vastly more problem instances than the others. In contrast to that, in the MP and IPP environment, classifying is more balanced between the agents. This has been obvious also for all other configurations that are not present in the figure. The exact reason for this kind of behavior could not be determined. It might be due to the specific structure of the problem types. Ultimately, all the effects described here prove again that the system, while producing acceptable classification results, is not yet free of flaws and needs further improvement .

5.9.2 Random Entry-Agent

As can be seen in Figure 5.11, very even, symmetric classification and delegation patterns are evolving when the entry-agent is selected randomly each cycle. The displayed graphs are complete graphs with each edge and each node having the same size, besides some statistical deviation. This illustrates that each agent is classifying and delegating the same amount of problem instances. A fact that is not very surprising since distinct classifications are distributed evenly among agents and good delegations are known to every agent. Any result different from a complete graph with balanced delegations would have been extremely surprising. Since all the collected data sets resulted in such a balanced, complete graph, only two of them are displayed in the figure.

5.10 Conclusion

XCS-DR is still a XCS, and capable of yielding the exact same classification results, as could be concluded from the single-agent experiments where it per-



(a) (b)

Figure 5.11: Classification and delegation patterns of XCS-DR with random entry-agent. 8-IPP, 5 agents (a); Woods2, 10 agents (b). All configuration parameters have been the same as in the corresponding performance experiments.

formed equal to XCSJava 1.0. As the number of agents rises, the performance of XCS-DR declines. In some environments more than in others. The classifications that XCS-DR evolves are equal to the ones that are evolving in XCSJava 1.0. This stems from the fact that both perform equal when only a single agent is applied to XCS-DR. As XCS-DR's agents have been provided with a high enough slot number during every experiment, the reason for the decline of performances must lie somewhere in the concept of a subdivided population with classifiers supporting delegations and how their introduction affects the overall system. This is backed up by the observation that XCS-DR tends to reinforce overgeneral, useless delegations and classifications. The emergence of the latter could partially be prevented by the tweak introduced in 3.2.3. However, the exact cause for the partial dysfunction of the evolution of classifiers could not be identified. It could be the fitness update mechanism or the action set formation or some other source. Ultimately, constitutes the introduction of delegations in a subdivided classifier population a significant increase in complexity of the overall system. Regarding that fact, is XCS-DR still performing satisfactory by classifying problem instances correctly with a high percentage and finding food in a maze reliably, even with high agent numbers.

Summary and Conclusion

This thesis has introduced and investigated a new kind of rule-based evolutionary online learning system. It addressed the problem of distributing the knowledge of a Learning Classifier System, that is represented by a population of classifiers. The result is a XCS-derived Learning Classifier System 'XCS with Distributed Rules' (XCS-DR) that introduces independent, interacting agents to distribute the system's acquired knowledge evenly. The agents act collaboratively to solve problem instances at hand. XCS-DR's design and architecture have been introduced and its classification performance has been evaluated and scrutinized in detail in this thesis. While not reaching optimal performance, compared to the original XCS, it could be shown that XCS-DR still yields satisfactory classification results. It could be shown that in the simple case of applying only one agent, the introduced system performs as accurately as XCS.

Chapter 1 supplied the reader with general background information about the field of LCS. The concept of LCS, its components and underlying principles have been discussed. Also, this chapter provided brief remarks about the historic development of the field and reviewed related work.

Chapter 2 introduced XCS, the system that has been extended. It was explained how XCS distinguishes between strength and accuracy of its classifiers and how all the components of the system interact to form a simple yet effective Learning Classifier System.

The following chapter discussed XCS-DR, the adapted XCS system that has been designed to fit the specific needs of a distributed population. A second kind of classifier, the delgation, has been introduced. Delegations differ from traditional classifiers by their action part as they propose the forwarding of a problem instance to another agent of the population. All the components of the original system such as the population, match set and prediction array have been adapted to facilitate interacting agents and enable accurate classifications.

Chapter 4 discussed the Java implementation of XCS-DR that has been derived from XCSJava 1.0, a Java implementation of XCS. The configuration of the program, its design and package structure and other relevant implementation details have been included in this part of the thesis.

The last chapter scrutinized the performance of the Java implementation of XCS-DR. It turned out that the system reaches the same performance results as XCSJava 1.0 if it applies only a single agent. But as soon as the agent number rises, XCS-DR performs inferior to the original. It could be concluded that the delegation procedure is still flawed and needs improvement for XCS-DR to reach optimal performance. Nevertheless, if one takes XCS-DR's higher complexity and prototype character into account, it still displayed satisfying performance results.

Future research on XCS-DR should first and foremost be directed towards improving the system's classification performance. Since its inferior performance is caused by the malfunctioning evolution of delegations, efforts should be undertaken to further understand and improve the whole delegation explore procedure. Outstanding issues that should be clarified are why overgeneral delegations are evolving, how the fitness update of the system could be improved, if there is a more accurate way to update the prediction value of a delegation, whether the action set formation could be altered and why the total numerosities of classifications are usually higher than the ones of delegations. Due to the increased inherent complexity of the system it is much harder to understand entirely than the original XCS. Hence, understanding the exact working of XCS-DR and all of its internal mechanisms would be essential to future research. Once the system performs as accurately as XCS, one could direct research towards making the agents more independent of each other respectively of the overall system.

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List of Figures

Erklärung

"Ich versichere, dass ich die vorliegende Arbeit selbständig und nur unter Verwendung der angegebenen Quellen und Hilfsmittel angefertigt habe, insbesondere sind wörtliche oder sinngemäße Zitate als solche gekennzeichnet. Mir ist bekannt, dass Zuwiderhandlung auch nachträglich zur Aberkennung des Abschlusses führen kann".

Leipzig, 31.03.2016